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Introduction

An introductory summary

Over the last decade, the total amount of assets under management of U.S. mutual funds has dramatically grown from \$9 trillion in 2005 to over \$15 trillion in 2015.[1] The increasingly important role of mutual funds within the financial system has led to a surge of research examining mutual fund behavior and its impact on the broader financial economy. This thesis adds to this research area (i) by studying how fire-sales by mutual funds can result in financial contagion, (ii) by examining the relationship between securities lending and fund risk, and (iii) by analyzing the trading activity of mutual funds in the last three days preceding their disclosure date.

In the first paper "Financial Contagion in the Mutual Fund Industry" (co-authored with Tim R. Adam), we explore fire-sales as a mechanism for the transmission of liquidity shocks across the mutual fund industry. Fire-sales emerge if institutions are forced to sell assets due to liquidity needs, which can result in temporary asset price declines (Scholes, 1972; Shleifer and Vishny, 1997; Coval and Stafford, 2007; Jotikasthira, Lundblad, and Ramadorai, 2012). By exploiting an exogenous shock to the closed-end fund industry, we document that some levered closed-end funds were forced to fire-sell portions of their assets in February 2008. Assets that were sold in response to this shock temporarily declined by up to -10% and infected initially unaffected open-end funds that were significantly invested in these fire-sale stocks. We find that the performance deterioration that resulted from these investments led to fund outflows, which triggered additional fire-sales by open-end funds. Hence, our paper provides evidence that a liquidity shock can spread through

[1] See Investment Company Institute (2016).

fire-sales from one financial sector to another. This emphasizes the potential risk of financial contagion inherent in the mutual fund industry.

The second paper "Securities Lending and Fund Risk: Evidence from Mutual Bond Funds" examines whether mutual bond funds increase their portfolio risk by reinvesting the cash collateral received in securities lending transactions in risky securities. The reinvestment of collateral is essentially a form of leverage because lenders remain exposed to price fluctuations of the lent securities. Due to the opacity of securities lending programs, many regulators have recently noted that the risks embedded in these programs are not well understood (e.g., International Monetary Fund 2015, Financial Stability Board 2012). This paper sheds light on these risks by examining the relation between fund risk and lending. Studying this relation is challenging as lending and fund risk are endogenous variables that depend on other unobserved factors. I address this concern by differentiating between funds using their lending agents. Fund risk should not be associated with lending if the agent of a fund runs a lending program, in which lending transactions are collateralized by *non-cash* securities. Moreover, I identify lending agents that are more likely to follow risky collateral reinvestment strategies by collecting information about the agents' lending losses over the sample period. These losses must have resulted from risky collateral reinvestments.

Consistent with the hypothesis that lending increases fund risk, I find that the risk of government bond funds is positively related to their lending activity. This relationship disappears if the lending agent relies on non-cash securities as collateral. In contrast, the risk-lending correlation is more pronounced for funds whose lending agent is more likely to reinvest the lending collateral riskily. These results suggest that securities lending programs should not be viewed as a risk-free way to generate income and, instead, should be carefully monitored by investors.

In the third paper "End-of-Period Trading by Mutual Funds" (co-authored with Hermann Elendner), we propose a novel way to measure the trading activity of mutual funds over the last three days of their reporting period. We use this measure to systematically analyze the motives for end-of-period trading and how these trades impact stock prices. Our results indicate that end-of-period trades are related to window dressing. Window dressing describes the activity of mutual funds to manipulate holdings shortly before the disclosure date in an attempt to mislead investors (Agarwal, Gay, and Ling, 2014; Lakonishok, Shleifer, Thaler, and Vishny, 1991). Consistent with this activity, heavy end-of-period traders tend to disclose a (lower) higher proportion of stocks with strong (poor) past performance. They further show higher backward holding return and rank gaps, which are the standard measures for window dressing in the literature. Some end-of-period trades also appear to be driven by the need to respond to sudden inflows and outflows (Coval and Stafford, 2007). We do not find evidence for portfolio pumping, which describes the behavior of artificially inflating stock prices through aggressive trading immediately before disclosure (Carhart, 1997). Moreover, funds with large end-of-period trades do not show superior performance, indicating that most trades at the end of the period are not related to funds possessing proprietary information.

When examining the relation between stock prices and end-of-period trading, we find that stocks with a large demand overhang experience price increases of about 20 bps over the last three days before the end of a reporting period. In June and December, this price appreciation reverts over the following month. These results are consistent with end-of-period trades causing temporary price pressure.

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Financial Contagion in the Mutual Fund Industry

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Abstract:

We show that a liquidity shock to closed-end funds can lead to liquidity withdrawals from open-end funds, thus causing a cascade of fire-sales. The failure of the market for auction rate securities in 2008 triggered asset sales at some highly levered closed-end funds. These asset sales led to temporary price declines of up to -10%. Open-end funds that held significant numbers of these fire-sale stocks experienced outflows, forcing them to sell assets. These forced sales induced additional price pressure. Our results show that financial contagion can originate in a relatively small sector of the mutual fund industry and spread to a much larger one.

Keywords: Mutual funds, closed-end funds, financial contagion, fire-sales, flow-performance relationship, auction rate securities

JEL-Classification: G01, G11, G14, G23, G28

1 Introduction

"The first sale can set off a cascade of fire-sales that inflicts losses on many institutions [...] reducing the financial system's capacity to bear risk."
— French, Baily, and Campbell (2010), Princeton University Press

Due to the strong interdependencies of our financial system, liquidity shocks can become contagious by spreading from one market to another. While much analysis has focused on explaining and understanding financial contagion in the banking industry, less attention has been paid to the question whether and how shocks can transmit across non-bank financial institutions, such as mutual funds. In this paper, we address this question empirically by examining whether 'fire-sale cascades' can explain the spillover of a liquidity shock from the closed-end to the open-end fund industry.

Fire-sales are forced asset sales triggered by liquidity needs, which can cause temporary asset price declines (Scholes, 1972; Shleifer and Vishny, 1997). Given that fire-sale assets are not only held by the selling institutions, they simultaneously cause temporary losses to the portfolios of others. If fund investors react to these losses by withdrawing liquidity, as predicted by the well-known flow-performance relationship (Sirri and Tufano, 1998; Chevalier and Ellison, 1997), they can spur a cascade of additional forced fire-sales at those funds.[1] For that reason, a liquidity shock at some funds can transmit through fire-sales to other, initially unaffected, institutions.[2]

To study fire-sale cascades as a channel of financial contagion, we proceed along the following line of inquiry. First, we use an exogenous liquidity shock in the closed-end fund industry to overcome the primary challenge of

[1] Coval and Stafford (2007) document that outflows can force mutual funds to sell at fire-sale prices.
[2] This argument has been made by Shleifer and Vishny (2011), but is not empirically examined by them.

distinguishing between unforced and forced sales. This shock only affected some levered closed-end funds and, hence, allows for a clear identification of initial fire-sales. In the second step, we examine whether these fire-sales result in outflows at open-end funds that were not directly affected by the initial shock. Such outflows can emerge if investors of open-end funds do not differentiate between a performance deterioration caused by fire-sales and performance losses that are caused by other factors, such as poor managerial investment decisions. The examination of the flow-performance relationship and whether this relationship is affected by the reason for poor performance is, therefore, a critical part of this paper. Finally, we test whether open-end funds that were exposed to initial fire-sales sell assets at fire-sale prices themselves.

To identify initial fire-sales, we exploit the failure of the auction rate security (ARS) market in February 2008, which resulted in a sudden increase in borrowing costs for some levered closed-end funds. As the shock only affected levered funds, it is an ideal setting to examine spillover effects to open-end funds, which typically do not rely on leveraged investment strategies. ARS are preferred equity instruments, which accounted for almost 70% of total fund leverage by the end of 2007. The coupon rate of ARS is determined weekly, bi-weekly, or monthly through an auction mechanism. In February 2008, the auction mechanism for ARS stopped working due to reasons that were exogenous to the closed-end fund industry. As a result, ARS dividend rates were set to pre-specified maximum rates, which on average were twice the rates determined through the regular auction mechanism. In response to this sudden increase in borrowing costs, closed-end funds redeemed 90% of their ARS leverage over the following two years. These leverage redemptions were financed by asset sales as closed-end funds replaced their ARS only partially by other debt instruments.[3] We use these sales to construct a variable on the stock level, called ‘selling pressure’. This measure captures the aggregate sales of all funds that redeem ARS in a given period and proxies for the extent of price pressure that a stock experiences due to fire-sales in the selling quarter.

Using the asset sales of 53 ARS-levered closed-end funds, we find that stocks in the two highest selling pressure quintiles experience 4-factor abnormal stock returns of -9.1% to -10.4% in the selling quarter.[4] This price drop is followed by strong price reversals over the next 12 months that almost completely offset the initial price depreciation. Such a reversal is consistent with a temporary price drop caused by fire-sales, but inconsistent with a permanent price drop due to new information.

Some open-end funds that are not directly affected by the failure of the ARS market are significantly exposed to these fire-sales. We measure this exposure using a variable called ‘fire-sale exposure’. Funds with the highest exposure to fire-sales (i.e. funds in the top fire-sale exposure quintile) hold, on average, 16% of their portfolio in stocks that belong to the highest two selling pressure quintiles. These investments are costly. On average the 3-month fund performance deteriorates by 1.1% per one standard deviation increase in fire-sale exposure. More importantly, these performance losses lead to significant fund outflows as most investors appear to be insensitive to the reason for poor performance. We, however, observe differences between investor classes. When open-end funds are exposed to fire-sales, we show that the flow-performance relationship is weaker for institutional than for retail investors. This differ-

[3] Anecdotal evidence suggests that some funds were unable to replace their ARS by other debt instruments. For example, the Denali and Calmos Strategic Total Return Fund writes: ’At this time, the Fund has not found an adequate alternative to replace the ARPs [a form of ARS]’ (The Denali Fund, N-CSRS, March 2008); ’Our ability to refinance all preferred shares with debt was constrained by regulations that require total assets in closed-end funds to be at least three times the amount of debt leverage’ (Calamos Strategic Total Return Fund, N-CSRS, June 2008).

[4] Our results are obtained using the event-study methodology by Kolari and Pynnönen (2010), which accounts for cross-sectional correlations of returns and inflated volatiles in the event window.

ence is not observable in other non-exposure periods and suggests that retail investors pay less attention to the cause of the performance deterioration.

Finally, we examine whether sales of open-end funds that are exposed to fire-sales show also return patterns that are consistent with fire-sales. For that purpose, we define, analog to the selling pressure variable for closed-end funds, a pressure variable for sales by open-end funds, which we call ‘cascade pressure’. The cascade pressure variable measures the fraction of shares sold in aggregate by all open-end funds weighted by each fund’s ‘fire-sale exposure’ during the previous quarter. Weighting by the fire-sale exposure means that we put more weight on sales of open-end funds that were strongly exposed to closed-end fund fire-sales. Consistent with fire-sale cascades, we find that stocks in the top cascade pressure quintile have on average negative abnormal returns of -6.4% (as measured by 4-factor alphas) in the selling quarter, even after we eliminate all stocks held by ARS-levered funds. This return pattern reverses in the quarter that follows. Our results suggests that fire-sales can spread from one market segment (stocks held by closed-end funds) to an initially unaffected market segment (stocks held by open-end funds), posing a potential threat to financial stability.

One concern that needs to be addressed is the possibility that the observed stock return patterns are driven by unobserved variables or events such as the financial crisis. We try to mitigate this concern by running placebo tests using two control groups. To construct the first group we use the sales of the same ARS-levered funds, but consider only periods in which they do not redeem their ARS leverage. Hence, we can compare sales of redeeming funds with non-redeeming funds in the same period. The second control group is based on sales by funds that were not levered by ARS leverage. Thus, these funds should not be impacted by the failure of the ARS market. We use the same method as before to calculate two placebo measures of selling pressure based on the sales by both control groups. We do not find evidence for fire-sales for any of the two measures.

The strong price reaction of stocks sold by ARS-levered funds raises the question whether the observed price drop is only a result of fire-sales by the closed-end fund sector, which is relatively small compared to the total mutual fund industry. While we believe that closed-end fund sales exerted significant price pressure, the price effect might have been amplified by front-running speculators such as hedge funds, as described by Brunnermeier and Pedersen (2005). Consistent with this argument, we observe a strong increase in short sales for stocks in the top selling quintile during the selling quarter, while we do not find any increase in short sales for the placebo groups.

Our paper relates to different strands of the existing literature. First, our study adds to the growing literature on fire-sales, which is pioneered by Shleifer and Vishny (1992), who describe how forced sales can drive market prices temporarily away from their fundamental values. The empirical literature has shown that fire-sales can occur in both financial and product markets. For example, Campbell, Giglio, and Pathak (2011) show that forced sales can occur in the housing market. Pulvino (1998) and Benmelech and Bergman (2011) document that airline companies near or in bankruptcy sell aircrafts below value. Coval and Stafford (2007) and Jotikasthira, Lundblad, and Ramadorai (2012) document temporary price declines in stocks that are sold by open-end funds experiencing severe outflows. Mitchell, Pedersen, and Pulvino (2007) and Aragon and Strahan (2012) find that forced sales by hedge funds affect asset prices and liquidity. The work closest to our project is the study by Tang (2014), who documents price declines of stocks held by levered closed-end funds that experience an unexpected increase in borrowing costs. We go beyond Tang's findings by providing evidence that these initial fire-sales can cause a cascade of additional fire-sales by open-end funds. We also differ from Tang in our identification strategy. In contrast to Tang, we do not only compare stocks of ARS-levered funds with stocks of non-ARS-levered funds in the year following the shock, but compare quarterly sales by ARS-levered funds during redemption periods with sales by ARS-levered funds during non-redemption periods.

Second, our paper is directly linked to the literature focusing on fire-sale cascades. Most related to our work are the models by Vayanos and Woolley (2013) and He and Krishnamurthy (2012, 2013). Vayanos and Woolley (2013) argue that initial price declines can be amplified by flow-induced fire-sales. He and Krishnamurthy (2012, 2013) develop two more general models, which explain how equity withdrawals from financial intermediaries can be reinforcing in a general equilibrium framework. Lou (2012) argues that fire-sale cascades can explain mutual fund performance persistence, stock momentum, and the smart-money-effect. In a summary paper, Shleifer and Vishny (2011) present anecdotal evidence for such cascades. Other papers focus on fire-sales cascades that emerge due to de-leveraging cycles. Such de-leveraging cycles can arise if falling prices cause (i) margin requirements to rise or funding supplies to decline (Brunnermeier and Pedersen, 2009; Brunnermeier and Sannikov, 2014; Dudley and Nimalendran, 2011), (ii) the value of debt collateral to decline (Gromb and Vayanos, 2002), or (iii) leverage levels to rise above self-imposed or regulatory limits (Kiyotaki and Moore, 1997; Stein, 2009). We add to this literature by showing that initial fire-sales in one market can trigger fire-sales in other, initially unaffected markets.

Third, studying fire-sales also contributes to the stream of literature that investigates the role of non-banks in financial contagion, excess co-movement of asset prices, and abnormal asset volatility. Barberis and Shleifer (2003) show that excess stock co-movement and volatility can be caused by funds with similar investment styles. Bartram, Griffin, Lim, and Ng (2015) find empirical evidence that stock co-movement is related to common mutual fund ownership. Barberis, Shleifer, and Wurgler (2005) and Greenwood (2005, 2008) argue that the sentiment and preferences of fund managers affect stock return correlations. Anton and Polk (2014) show that two unrelated stocks can experience similar negative returns if they are held by the same funds with strong outflows. Greenwood and Thesmar (2011) show that non-fundamental stock volatility can be explained by correlated liquidity withdrawals from mutual funds. Boyson, Stahel, and Stulz (2010) find that hedge fund returns correlate more strongly as fundamentals would suggest because of common shocks to funds' funding situations. While these studies provide evidence that stock returns are strongly linked and affected by mutual fund behavior and ownership in general market conditions, Manconi, Massa, and Yasuda (2012), Hau and Lai (2013) and Adams, Füss, and Gropp (2014) emphasize the importance of funds in transmitting liquidity shocks. Manconi et al. (2012) argue that funds that were invested in both secured bonds and corporate bonds were largely responsible for spreading the crisis from the secured bond market to the corporate bond market. Hau and Lai (2013) find that the shock to bank stocks in the recent financial crisis spilled-over to non-bank stocks because of outflows at funds that were invested in both assets. Adams et al. (2014) quantify risk spillovers from hedge funds to banks and insurance companies. Our research will be the first to show that a shock to closed-end funds can spread to open-end funds and the assets they hold.

Finally, our paper is connected to studies that inquire the flow-performance relationship that was first documented by Sirri and Tufano (1998) and Chevalier and Ellison (1997). Del Guercio and Tkac (2002) show that investors of pension funds react more strongly to risk-adjusted performance measures, while mutual fund flows react more strongly to raw returns. James and Karceski (2006) provide evidence that flows respond less strongly to past performance when the fund is an institutional opposed to a retail fund. Huang, Wei, and Yan (2007), Ivković and Weisbenner (2009), and Chen, Goldstein, and Jiang (2010) find that the flow-performance relationship is affected by the level of participation costs, expenses, and the funds' asset compensation, respectively. We add to this literature by examining whether the flow-performance relationship is sensitive to the reason for poor performance.

The remainder of this paper is structured as follows. In Section 2, we describe the experimental design and our main variables, Section 3 covers the data and data sources. Section 4 reports our empirical results. In Section 5, we present robustness and additional tests. Section 6 concludes.

2 Experimental design and variables

2.1 Fire-sales by ARS-levered funds

In the first part of our analysis, we study fire-sales by levered closed-end funds. We identify these fire-sales by exploiting an unexpected shock to the borrowing costs of some levered funds, which resulted in de-leveraging and portfolio liquidations. Relying on an exogenous shock for the identification of fire-sales is advantageous as it allows us to refrain from fund flows, which are potentially endogenous.

2.1.1 The failure of the auction rate security market

In early 2008, some levered closed-end funds were exposed to a funding shock, when the auction rate security (ARS) market collapsed. ARS are preferred equity securities, which were used by 21% of our sample funds and accounted for 70% of total fund leverage by the end of 2007. The feature that distinguishes ARS from other sources of leverage is that the dividend yield is reset weekly, bi-weekly, or in rare cases monthly through an auction mechanism. In such an auction, all existing bids are ranked and the lowest rate at which all ARS can be (re-)allocated at par value establishes the clearing rate, which is valid up to the next auction date. Should the auction mechanism fail, the fund must pay a pre-specified maximum dividend rate on its outstanding ARS. An auction failure is usually caused by a demand-supply imbalance, which prevents the market from clearing.

Before 2008, auction failures of ARS were extremely rare. A special report of Moody's (2008), for example, recorded only 44 failures in over 100,000 auctions. Starting in mid February 2008, however, the market for ARS securities suddenly collapsed and almost all auctions began to fail. The auctions in our sample showed similar failures.[5] The main reason for the ARS market collapse was an unexpected liquidity withdrawal by brokers-dealers (Han and Li, 2009; Tang, 2014). Brokers-dealers regularly supported auctions by buying ARS on their own accounts and acting as a market maker. When they withdrew collectively from the market, there was no buffer for demand and supply imbalances, which caused the liquidity in the ARS market to quickly dry up. Consequently, auction failure became a permanent symptom of the ARS market.

When the ARS market collapsed, the dividend rate of ARS jumped to their pre-specified maximum rates. Figure 1 captures the development of these rates around the failure of the ARS market in February 2008. Since our data set does not contain dividend rates of the sample funds before the ARS market failure, we complement our data with the SIFMA Auction Rate Preferred 7-Day Index. This index contains self-reported data from actual ARS issues (including issues by other institutions than closed-end funds). As shown, the average dividend rate of the SIFMA index was relatively stable and fluctuated at about 0.75 of the 1-week US LIBOR rate before the ARS market failure. Beginning in February, however, the index suddenly increased to a maximum

[5] One ARS issue was not subject to auction failure because the whole issue was bought by an affiliated investor.

of about 1.4 of LIBOR.[6] This corresponds well to the average maximum dividend yield observed among our sample funds, which amounts to about 1.5 of LIBOR in the periods subsequent to the ARS market failure. This suggests that our sample funds experienced on average almost a doubling of their borrowing costs. Since the failure of the ARS market was predominantly driven by liquidity needs of brokers-dealers and since other non-funds institutions were similarly affected, this increase in funding costs was plausibly exogenous to the mutual fund industry.

*** Insert Figure 1 about here ***

In response to the sudden increase in borrowing costs, many funds redeemed their outstanding ARS, as illustrated in Figure 2.[7] Between February 2008 and February 2010, the total volume of outstanding ARS (solid blue line) declined by about 12 billion, which represents a reduction of almost 90%. The number of funds that used ARS as a source of leverage (green dashed line) shrunk in a similar manner. The dotted-dashed red line, which shows the volume of non-ARS liabilities, indicates that funds partially replaced their ARS by other liability types. In fact, about 12% of our sample funds replaced their ARS completely by other debt instruments. In contrast, 14% did not raise any (non-ARS) debt. Most funds substituted only partially. One reason for this incomplete substitution is that the SEC imposes lower restrictions on ARS-leverage (100% of TNA) when compared to debt-leverage (50% of TNA).[8] Incomplete substitutions, however, may also have resulted from capital supply

[6] Note that the fluctuation in the ARS index after the failure of the ARS market are caused by a weekly changing composition of issues. Hence, the index strongly depends on the fraction of failed auctions used to calculate the index at a given date.

[7] Most ARS issues are perpetual, but redeemable at the fund's option.

[8] In unreported tests we, however, do not find evidence that sales by funds with more than 50% leverage result in larger price effects.

frictions.[9] Since closed-end funds did not completely substitute their ARS-leverage, they had to sell assets to finance their ARS redemptions.[10] We will use these sales to identify stocks that were fire-sold.

*** Insert Figure 2 about here ***

2.1.2 Treatment and control groups

One advantage of our setting is that we observe sales of ARS-levered funds during periods in which they reduced their ARS and during periods in which they did not alter their ARS positions. While funds needed to sell assets to finance ARS reductions in redemption periods, they faced no selling pressure in non-redemption periods. We use this information to differentiate between sales by ARS-levered funds in redemption (treatment group) and non-redemption periods (control group I). Moreover, as an additional control group, we also examine the sales by closed-end funds that did not rely on ARS-leverage and, hence, faced no direct increase in borrowing costs. Thus, we can examine the sales of three different groups:

(i) Treatment: Sales of *ARS-levered* funds in *ARS redemption periods*

(ii) Control I: Sales of *ARS-levered* funds in *non-ARS redemption periods*

(iii) Control II: Sales of *non-ARS-levered* funds

We expect fire-sales only to be present when studying stock sales of ARS-levered funds in ARS redemption periods (treatment group), while we should

[9] Since the failure of the ARS market was triggered by broker-dealers that were impacted by tightening credit markets themselves, it is not surprising that closed-end funds could not easily replace their ARS by bank leverage. We also found anecdotal evidence for credit supply frictions in fund reports. For example: 'At this time, the Fund has not found an adequate alternative to replace the ARPs [A form of ARS]' (The Denali Fund, N-CSRS, March 2008); 'Our ability to refinance all preferred shares with debt was constrained by regulations that require total assets in closed-end funds to be at least three times the amount of debt leverage' (Calamos Strategic Total Return Fund, N-CSRS, June 2008).

[10] The average cash position of our ARS-levered funds is less than 1% of total assets and, hence, plays no significant role in the financing of ARS redemptions.

not find similar evidence in both control groups. Since funds redeemed their ARS redemptions in different time periods, we can examine the return patterns of (forced) asset sales throughout the sample period from 2008 to 2010. This mitigates concerns that price movements of stocks in the treatment group are driven by reasons unrelated to fire-sales.

2.1.3 Identification of fire-sales

We identify fire-sale stocks by constructing a time-varying pressure measure for each stock j, similar to the pressure measure used by Coval and Stafford (2007). This measure is based on the selling behavior of ARS-levered closed-end funds during redemption periods (treatment group).

$$Selling\ pressure(TG)_{j,t} = \sum_{i}^{i \in ARS} \left(\frac{max(-\Delta Shares_{i,j,t}, 0)}{NOSH_{j,t}} \middle| Redemption_{i,t} = 1 \right) \tag{1}$$

$\Delta Shares_{i,j,t}$ is fund i's sales of stock j between quarter $t-1$ and quarter t. $NOSH_{j,t}$ is stock j's total shares outstanding at quarter t. $Redemption_{i,t}$ is a dummy variable that equals one if fund i reduces its outstanding ARS between quarter $t-1$ and quarter t. Intuitively, the selling pressure measure captures the aggregate sales of stock j by all ARS-levered funds, which redeemed ARS in a given quarter (treatment group). If the selling pressure measure is high, the stock is a potential fire-sale stock in the respective quarter. As noted earlier, closed-end funds redeemed their ARS in different time periods. Hence, the selling pressure measure has substantial cross-sectional and time-series variation.

We use an analogous procedure to calculate two placebo selling pressure measures using the stock sales of ARS-levered funds during non-redemption periods (control group I) and using the sales of non-ARS levered funds during the entire sample period (control group II). As those sales were not triggered by the need to finance ARS redemptions, there should be no evidence for fire-sales for these transactions.

$$Selling\ pressure(CGI)_{j,t} = \sum_{i}^{i \in ARS} \left(\frac{max(-\Delta Shares_{i,j,t}, 0)}{NOSH_{j,t}} \middle| Redemption_{i,t} = 0 \right) \tag{2}$$

$$Selling\ pressure(CGII)_{j,t} = \sum_{i}^{i \in non-ARS} \left(\frac{max(-\Delta Shares_{i,j,t}, 0)}{NOSH_{j,t}} \right) \tag{3}$$

2.1.4 Analyzing fire-sale return patterns in event studies

We follow Coval and Stafford (2007) and analyze stock return patterns in event studies to examine whether our selling pressure measure truly identifies fire-sale stocks. Fire-sold stocks should experience negative return in the selling quarter followed by subsequent reversals. Such a reversal is consistent with a temporary price drop caused by fire-sales, but inconsistent with a permanent price drop due to a change in investors' expectations. To analyze stock returns, we split our stocks into five quintiles according to each stock's selling pressure. The probability of detecting fire-sale patterns should increase as we move along these quintiles. We define for each stock an event quarter, which is the quarter in which the stock's selling pressure is the highest during the sample period.

*** Insert Figure 3 about here ***

Figure 3 shows the distribution of these event quarters for the top selling pressure quintiles of treatment and control groups. While the event quarters of control group II (non-ARS levered funds) are quite equally distributed throughout the sample period, most event quarters of the treatment and control group I are found between the second quarter of 2008 and the first quarter of 2009. Due to this event clustering, abnormal returns are likely correlated in the cross-section. Moreover, test statistics might be misspecified due to event-induced volatility. To account for both, cross-correlation and variance inflation, we use a recent event study methodology proposed by Kolari and Pynnönen (2010), which we detail in Appendix A.4.[11]

For each group and quintile, we conduct separate event studies, in which we test for abnormal returns in the event quarter and the following 12 months. Abnormal returns are measured by 4-factor alphas, which account for the stocks' risk exposure to the following four factors: (i) the market, (ii) the size, (iii) the value-to-book, and (iv) the momentum factor. The betas used to calculate these alphas are estimated using daily returns over the year preceding the ARS market failure. The test-statistics are computed using the methodology of Kolari and Pynnönen (2010) and are based on the average cumulative abnormal return of all stocks in the respective group, quintile, and event period.

2.2 The impact of fire-sales on open-end funds

To investigate whether fires-sales by ARS-levered closed-end funds can lead to financial contagion, we study the impact of fire-sales on open-end funds that were not directly affected by the ARS market failure. If fire-sales negatively affect asset prices, portfolios of open-end funds with large investments in these stocks should lose in value. We, therefore, start by investigating whether open-end funds with high exposure to fire-sale stocks show abnormal performance losses. Such a performance deterioration can lead to fund outflows if investors ignore the reason for poor performance and withdraw liquidity from the fund,

[11] We do not use non-parametric event study tests or a portfolio approach as the test statistic of Kolari and Pynnönen (2010) is more powerful in long-horizon event studies.

as predicted by the well-know flow-performance relationship (e.g. Chevalier and Ellison, 1997; and Sirri and Tufano, 1998). Thus, the main objective of this section is to examine whether the flow-performance relationship is affected by the reason for poor performance.

To examine the impact of fire-sales on the performance and flows of open-end funds, we construct a variable that measures the extent to which an open-end fund is exposed to fire-sale stocks, which we call 'fire-sale exposure'.

$$\begin{aligned} Monthly\ selling\ pressure\ (TG)_{j,t} &= \sum_{m=0}^{2} \frac{1}{3} \cdot Selling\ pressure_{j,t+m} \\ FS\ exposure_{i,t} &= \sum_{m=0}^{2} \sum_{j} Monthly\ selling\ pressure\ (TG)_{j,t-m} \cdot w_{i,j,t-3} \end{aligned} \tag{4}$$

Note that the variable selling pressure (TG) at period t measures stock j's price pressure during the last *three* months. To compute a monthly selling pressure variable, we take the average of all selling pressure measures that affect a stock in a given month, i.e. the selling pressure of t, $t+1$, and $t+2$.[12]

Fund i's fire-sale (FS) exposure equals the sum of each stock j's monthly selling pressure (TG) in quarter t weighted by fund i's relative investment in the stock at the beginning of the quarter ($w_{i,j,t-3}$). Intuitively, an open-end fund with high fire-sale exposure holds a large proportion of fire-sale stocks. We hypothesize that the fire-sale exposure measure is negatively related to fund performance. This relation is not mechanically because open-end funds could avoid a performance loss by selling a stock before the fire-sales takes place or make other profitable investments. We then test in our main analysis whether the flow-performance relationship holds even if the performance deterioration appears to be driven by price movements due to fire-sales.

[12] We need to compute the monthly selling pressure variable since funds report to their shareholders in different calendar months.

2.3 Fire-sale cascades

Coval and Stafford (2007) show that outflows at open-end funds can result in fire-sales. Fire-sold stocks depreciate in the selling quarter and show significant reversals in the subsequent months. If fire-sales by closed-end funds cause outflows at open-end funds, as predicted in the previous section, assets sold by open-end funds with high fire-sale exposure should show similar fire-sale patterns during the outflow quarter. To test this hypothesis, we construct a pressure measure using our sample of open-end funds, which we call 'cascade pressure'.

$$Cascade\ pressure_{j,t} = \sum_{i}^{i \in Open} \frac{max(-\Delta Shares_{i,j,t}, 0) \cdot FS\ exposure_{i,t-3}}{NOSH_{j,t}} \quad (5)$$

Intuitively, the cascade pressure measure captures the proportion of shares sold in aggregate by all open-end funds weighted by each fund's fire-sale (FS) exposure during the previous quarter. We weight by the funds' fire-sale exposure to give more weight to sales by open-end funds that hold a larger proportion of ARS fire-sales stocks in their portfolios. Large sales of stocks by open-end funds that were heavily invested in ARS fire-sale stocks are likely fire-sale candidates. To isolate the cascade pressure effect from a potential price impact due to sales of closed-end funds, we will analyze stock returns only for stocks that were not held by ARS-levered closed-end funds in the previous quarter. Using the same event study methodology as described in Section 2.1.4, we will examine whether stocks in the highest cascade pressure quintile have abnormal stock returns in the selling quarter and show subsequent reversals.

3 Data

Our sample period spans from February 2008 to February 2010 to cover the period in which the majority of ARS leverage is redeemed in response to the ARS market failure in February 2008.[13] Our data set consists of two subsamples: Closed-end and open-end funds.

We use web-crawling techniques to extract information on closed-end funds from N-SAR forms, which have to be filed by all U.S. investment companies in a semi-annual frequency. N-SAR forms contain a large number of fund characteristics and detailed balance sheet data.[14] Closed-end funds are identified through question 27 (Q27) on the N-SAR form. We drop all entries for which the date of filling or the fund name is not extractable as well as records for which total assets or net assets are zero, negative, or not available. We only keep funds that primarily invest in equity securities (N-SAR Q66) since our analyses require detailed holding data that are more extensive for equity funds.[15] Using Q69 on the N-SAR form and the inspection of fund names, we exclude index and real estate funds. To eliminate funds that only show up in our sample due to misreporting, we only keep funds for which we have at least five consecutive observations.

To obtain access to quarterly fund holdings, we carefully merge this data with the Morningstar Direct and the Thomsaon Reuters S12 Ownership Database using fund names and tickers. We follow Coval and Stafford (2007)

[13] In some descriptive statistics we also present data of before February 2008 to describe the evolution of leverage over time.

[14] To ensure the quality of our data, we manually inspect a random sample of 100 N-SAR fillings, which show no identifiable extraction error.

[15] Although focusing on relative liquid equity markets, makes it harder to identify mispricing, several studies (e.g. Coval and Stafford 2007, Jotikasthira et al. 2012) document that stocks sometimes sell at fire-sale prices.

and require funds to report a minimum of 20 holdings at least once during the sample period.[16]

Since data on ARS leverage is not available in any standard database, we hand-collect quarterly ARS positions as well as quarterly total net assets for all closed-end funds in our sample from SEC N-CSR(S) and N-Q fillings. We use the latest available information on ARS leverage before February 2008, the failure of the ARS market, to differentiate between ARS-levered funds that were exposed to the funding shock and non-ARS-levered funds. Our closed-end equity fund sample consists of 53 ARS-levered and 155 non-ARS-levered funds.

To construct our open-end fund data set, we collect all open-end funds available in the CRSP Survivor-Bias-Free US Mutual Fund Database. Using MFLINKS we match this data to quarterly holdings available in the Thomson Reuters S12 Ownership Database. We eliminate all index funds (as defined by CRSP) and non-equity funds, which we identify by Thomson's investment objective code. We address the incubation bias in the CRSP database identified by Elton, Gruber, and Blake (2001) and Evans (2004) by removing observations of funds with less than 5 million assets under management in the previous month. Similar as with the closed-end fund data, we remove funds that never report more than 20 holdings throughout the sample period. We are left with 1,469 open-end equity funds.

We match all open-end and closed-end fund holdings to the CRSP Stock Database using 8-digit CUSIPs to obtain stock prices, returns, and other stock characteristics. Our sample includes 8,746 different stocks, which represent 70.7% of all common stocks (share code 10 or 11) contained in the CRSP Stock Database.

[16] Coval and Stafford (2007) argue that the holdings of funds with less than 20 holdings are less reliable.

The paper also relies on several other data sources. Dividend yields of ARS issues are obtained from the Securities Industry and Financial Markets Association (SIFMA). 1-week US LIBOR as well as 1-month Treasury Bill rate are provided by St. Louis Fed. To calculate abnormal returns, we use the market, size, value-to-book, and momentum factors from the Fama/French website. The liquidity factor of Pastor and Stambaugh (2003), which is used to estimate liquidity betas, is downloaded from Lubo Pastor's research website. Short sale data on stocks are obtained from the Bats Exchange website.[17]

The data is used to construct a number of variables that are described and defined in Appendix A.I. All continuous variables are winsorized at the 1% levels to alleviate the effect of outliers.

4 Results

4.1 Descriptives

Table 1 shows descriptive statistics for ARS-levered and non-ARS-levered as well as open-end funds in the last quarter before the failure of the ARS market in February 2008. As observed in Panel A, the ARS-levered and non-ARS levered funds in our sample are considerably large despite their closed-end structure. While total assets of ARS-levered funds amount to $1,000 million on average, non-ARS-levered funds manage on average assets worth of $558 million. This difference is partially attributable to different levels of TNA ($679 million compared to $509 million), but is predominantly a result of distinct leverage policies. ARS-levered funds use considerably more leverage averaging at 51% of TNA, compared to non-ARS-levered funds (9%). Among the ARS-levered funds, ARS-leverage accounts for the majority of leverage amounting to almost 45% of TNA on average. This is important for our identification

[17] Unreported analyses reveal that the short sale data of the Bats Exchange website has 90% correlation with the short sale data from NASDAQ.

strategy as it shows that ARS-levered funds were strongly exposed to the failure of the ARS market. In contrast, the amount of other leverage accounts only for 6% of TNA and is comparable to the average amount of other leverage used by non-ARS-levered funds (9%).

The TNA of open-end funds are on average significantly higher compared to both closed-end fund groups (1,135 million). However, since open-end funds usually do not use leverage, the amount of total assets is comparable to the assets managed by ARS-levered funds.

We observe strong differences in the turnover ratios across all three groups. The turnover ratio of ARS-levered funds (22%) is on average about half the turnover ratio of non-ARS-levered funds (42%) and about a quarter of the turnover ratio of open-end funds (85%). The comparably lower turnover ratio of closed-end funds is consistent with the findings of Deli and Varma (2002).

Panel B compares the holding characteristics of the sample funds. Both closed-end fund groups as well as the open-end funds in our sample invest in stocks that have similar market capitalization and trading volumes. Stocks held by open-end funds tend to have slightly lower bid-ask spreads than both closed-end fund groups. Examining the market beta, we observe that open-end funds and non-ARS levered funds tend to have a market beta close to one. In contrast, ARS-levered funds appear to invest in stocks with slightly lower market betas (0.8). This is consistent with the idea that ARS-levered funds buy low beta stocks and use leverage to increase their market exposure (Frazzini and Pedersen, 2014).

*** Insert Table 1 about here ***

The differences observed in leverage, turnover, and the holdings indicate that ARS-levered and non-ARS-levered funds follow different investment strategies and, hence, are only imperfect candidates for control and treatment group. For this reason, we use a different identification strategy as Tang (2014), who compares returns of stocks held by ARS-levered with the stocks held by non-ARS-levered funds. Instead, we compare stock *sales* by ARS-levered funds during redemption periods (treatment group) with stock sales during non-redemption periods (control group I) and complement this analysis by studying stock sales by non-ARS-levered funds (control group II). Using this strategy, we search for fire-sales in periods in which ARS-levered funds sold assets to finance their ARS redemptions.

Consistent with this argument, Panel A of Table 2 shows that the reduction of total investments is unusually strong for ARS-levered funds during redemption periods. On average, total investments shrink by 13.7% in ARS redemption periods, while total investments fall only by 3.88% if ARS-levered funds do not redeem. The stronger decrease in total investments stems at least partly from large reductions in ARS-leverage of about 16.5% on average. ARS-levered funds in redemption periods seem to be unable to substitute their ARS-leverage by other debt financing. Therefore, total leverage decreases by 6.3%. For comparison, the leverage ratio decreases only by 1.1% on average in non-redemption periods. During the same period, the assets of non-ARS-levered funds only decline by about 5% and leverage remains fairly stable. This evidence suggests that ARS-levered funds sold assets to finance their redemptions. Note that our results also indicate that assets are not sold before the redemption quarter to strategically avoid fire-sale costs.

*** Insert Table 2 about here ***

For our identification strategy, it is important that our treatment and control groups sell the same type of stocks. Panel B shows characteristics for stocks that are sold and not sold by all three groups. Overall, the sales of ARS-levered funds in ARS redemption periods are comparable to the sales in non-redemption periods. The stocks are of similar size, experienced in the past small negative returns of between -1.7% and 2.2%, and differ not substantially in terms of volatility, dividend yield, and market beta. Sales in ARS redemption periods tend to have a slightly lower trading volume and a smaller relative bid ask spread. In contrast, sales of non-ARS levered funds differ more strongly from the two other groups. Non-ARS-levered funds tend to sell bigger stocks, stocks with more turnover, higher past stock volatility, and higher dividend yield. These differences are consistent with our previous observations that non-ARS-levered funds and ARS-levered funds follow different investment strategies and justify our approach to compare ARS-levered funds during redemption with ARS-levered funds during non-redemption periods.

4.2 Fire-sales by ARS-levered funds

4.2.1 Selling pressure and stock returns

In this section, we study whether the failure of the ARS market resulted in fire-sales. As described in Section 2.1, we identify fire-sales by studying the sales of ARS-levered funds in periods in which they had to finance their ARS redemptions and, hence, were likely forced to liquidate assets.

In Panel A of Table 3, stocks are split into five quintiles according to the selling pressure measure, which captures the extent to which a stock is sold by ARS-levered funds during their ARS redemption periods. The highest quintile contains stocks that experience the highest selling pressure during the sample period and, hence, are the most likely fire-sale candidates. The lowest quintile, in contrary, contains stocks with the lowest selling pressure.[18] We define the 'event quarter' of a stock as the quarter in which its selling pressure was the highest during the sample period and document (cumulative) 4-factor adjusted stock returns for the event quarter and the following 12 months.[19] For statistical inference, we rely on the event study methodology of Kolari and Pynnönen (2010), which accounts for cross-sectional return correlations across stocks and inflated return volatility in the event period.

*** Insert Figure 4 about here ***

Consistent with fire-sales, we find that stocks with high selling pressure show negative and statistically significant abnormal returns in the event quarter, i.e. the quarter, in which they are sold by ARS-redeeming funds. These abnormal returns are economically large. Stocks that are sorted into the fourth and fifth quintile experience on average abnormal stock returns of -9.1% and 10.4%, respectively (see Figure 4 for a graphical representation of the fifth quintile). Importantly, the price decline observed in the upper two quintiles is followed by substantial price reversals. In the 3 to 12 months that follow the fire-sale quarter, stock returns reverse by an average abnormal stock return of 14.3% for the fifth and an average abnormal stock return of 19.1% for the fourth quintile.[20] Such a reversal is consistent with a temporary price drop caused by fire-sales, but inconsistent with a permanent price drop due to a change in investors' expectations.

Note that in the fifth quintile both, the price decrease as well as the price reversal, are only significant at the 10% level despite their high economic

[18] Stocks that were not sold by ARS-levered funds during ARS redemption periods are not included.

[19] Results are robust if we study 1-factor or 5-factor abnormal returns.

[20] Note that stock prices in the fifth quintile continue to fall in the subsequent three months after the fire-sale quarter. Two possible reasons for this price decline include fire-sale cascades, which we examine in Section 4.4, and predatory trading, for which we present evidence in Section 4.2.2.

significance. This comparably low level of significance is caused by the choice of our event study methodology, which accounts for potential correlations across returns. Given that event dates in the fifth quintile are more clustered when compared to the other quintiles, t-statistics in this quintile need to be adjusted more strongly for potential cross-correlations.[21] We believe this conservative approach is important to make sure that t-statistics are not biased upwards.

We find similar downward patterns for the third quintile (-9.3%), but no subsequent reversals. Hence, the price drop in this quintile is not explainable by price pressure.[22] Among the stocks with low selling pressure (lowest two quintiles), we do not observe any statistically significant price change. Hence, stock prices appear to be only affected if they are heavily sold during redemption periods.

Overall, our results indicate that the sudden need to repay leverage can result in significant downward price pressure on individual stocks that is not explainable by information based theories.

*** Insert Table 3 about here ***

A valid concern is that the observed price patterns are spurious or driven by other contaminating events such as the financial crisis. One feature of our identification strategy that mitigates this concern is the fact that our sample funds redeem their ARS in different time periods. Hence, the individual event quarters differ across stocks.

We further address this issue by conducting two placebo tests. For that purpose, we repeat the analysis of Panel A, but construct quintiles according to

[21] For example, the estimated cross-correaltion in the fifth quintile is 0.02, while it is below 0.004 for the other quintiles. If we do not adjust for this correlation across returns, the price effect documented in the fifth quintile is significant to the 1% level.

[22] Coval and Stafford (2007) report similar price effects resulting from voluntary trades. They believe this effect to be driven by funds bringing information into prices or by unloading poor performing stocks.

two placebo selling pressures (defined in Section 2.1). These placebo measures are based on the sales of ARS-levered funds during non-redemption periods (control group I) and the sales of non-ARS-levered funds (control group II). As both groups had no need to finance ARS redemptions during the event quarter, we can interpret the stocks in the highest quintiles as those stocks that were heavily, but voluntarily sold within the sample period. Panel B and C reveal that there is no evidence for fire-sales in both placebo tests. For control group I, we find no price effect in the event quarter for all quintiles except the third (Panel B). For control group II, we observe a weak but significant price drop in the event quarter for the top quintile (Panel C). However, reversals do not follow on any of these price decreases. This suggests that the price drop is not caused by fire-sales, but rather the result of funds selling due to information or in an attempt to eliminate underperforming stocks. Therefore, in contrast to our treatment stocks, sales of our control groups show no price movements consistent with fire-sales.

4.2.2 Predatory trading and characteristics of fire-sale stocks

Although about \$190 billions of assets were managed by U.S. closed-end funds by 2008 alone, the industry is relatively small compared to the open-end fund industry with total net assets of about \$9,600 billions.[23] This difference might raise the question whether closed-end funds can create sufficient price pressure to cause the observed price drop.

We present two arguments to address this question. First, we want to draw attention to the magnitude of sales by ARS-levered funds during redemption periods. During ARS-redemptions total investments by ARS-levered funds shrink by about 13.7% or \$155 million on average (see Table 2). When multiple funds need to liquidate such a significant proportion of their assets during adverse market conditions and low market liquidity, which predomi-

[23] Investment Company Fact Book, 2009.

nated during the sample period, it seems reasonable that stock prices are not immune to these transactions.

Second, and even more importantly, we believe that the price pressure effect created by ARS-levered funds was amplified by front-running speculators, such as hedge funds. Brunnermeier and Pedersen (2005) show that front-running or - as they label it - predatory trading can lead to additional price overshooting and reduced market liquidity.

*** Insert Figure 5 about here ***

The first graph of Figure 5 provides descriptive evidence for front-running by displaying the short sale volume around the event quarter for stocks in the highest selling pressure quintile, i.e. for those stocks that showed strong price declines. The red dashed line indicates that the short-sale volume amounts to about 0.05% of shares outstanding six months before the event quarter. About three months before the event quarter short sales start to increase continuously and the volume reaches a level of about 0.4% one month after the fire-sale quarter. In the months thereafter, short sales decrease again to a volume similar to the level before the event quarter. The increase before the event quarter is consistent with predatory speculators trying to exploit the funds' selling needs in advance of the transaction.

To ensure that the increase of short sales is not only a byproduct of the financial crisis or some other phenomena in the sample period, Figure 5 also contains the short sale volume for the top quintile of our two placebo selling pressures, which we calculate using sales of ARS-levered funds during non-redemption periods (control group I) and using sales of non-ARS-levered funds (control group II). For control group I, the fluctuations of the short sale volume seem to be unrelated to the stocks' selling pressure. For example, there is virtually no increase in short sales during the event quarter. The short sale volume of control group II is stable throughout the considered time period. Hence, there is no evident link between short-sales and selling pressure in the two control groups.

While this evidence is indicative for front-running, it is only feasible if speculators had access to two pieces of information: (i) The period in which the fund was forced to sell and (ii) the position that was sold by the pressurized fund. The first piece of information is publicly known as funds announced their planned ARS-redemptions in advance. We argue that the speculator could infer the second piece of information from the funds' past holdings, which are known to be sticky.

*** Insert Table 4 about here ***

Table 4 presents evidence that supports our argument. Stocks that were held in large proportions by ARS-levered funds one quarter before the ARS market failure turn out to experience higher selling pressure and end up in the top selling pressure quintile with higher probability. Hence, a speculator could easily profit from the funds' selling needs by short-selling stocks in which ARS-levered funds had the highest ownership. While the ownership by ARS-levered funds is by far the most predictive variable, fire-sale stocks also tend to have a smaller market capitalization, higher dividend yields, higher trading volumes, and a lower sensitivity to the aggregated market liquidity. The latter two findings support the idea that funds tried to mitigate fire-sale costs by selling more liquid assets.

4.3 The impact of fire-sales on open-end funds

4.3.1 Univariate results

Although open-end funds are not directly affected by the collapse of the ARS market, open-end funds are indirectly affected by the shock if they are invested in stocks that experience price pressure due to fire-sales by ARS-levered funds. We measure the exposure to fire-sales using a variable called 'fire-sale exposure', as defined in Section 2.2. Our main objective in this section is to examine whether this exposure leads to fund outflows at open-end funds. These outflows may emerge if fund investors withdraw liquidity from funds whose performance suffered from investments in fire-sale stocks. The empirical fact that fund investors respond to fund performance has been well documented by several studies in the literature (see e.g. Chevalier and Ellison, 1997 and Sirri and Tufano, 1998). The main question, therefore, is whether investors react to poor performance even if the performance deterioration results from an exposure to fire-sale stocks. This question is important as outflows can trigger additional fire-sales (Coval and Stafford, 2007).

*** Insert Table 5 about here ***

We start by analyzing this question descriptively. For that purpose, we sort the open-end funds in our sample into five quintiles according to each fund's level of fire-sale (FS) exposure. We then document (i) the average fire-sale exposure, (ii) the average proportion of the portfolio invested in stocks that were fire-sold by closed-end funds, (iii) the average 3-month abnormal fund performance, and (iv) the average netflows in the subsequent quarter. 3-month abnormal fund returns are calculated by adjusting fund returns by the weighted return of all sample funds.[24] All other variables are defined in Appendix A.I.

As shown in in Table 5 and confirming the validity of our measure, open-end funds with the lowest fire-sale exposure (quintile 1) have less than 1% of their assets invested in stocks whose selling pressure is in the top three quintiles. Hence, their portfolios are essentially not affected by any price pressure induced

[24] We do not measure performance using factor models as the existing literature shows that investors react predominantly on raw returns relative to the market.

by closed-end fund fire-sales. In contrast, open-end funds with the highest fire-sale exposure (5. quintile) have about 8% of their holdings invested in stocks belonging to the fifth selling pressure quintile and about 9% of the assets invested in stocks belonging to the fourth quintile. Since these stocks experience significant price declines of up to 10%, these investments should be costly. Consistent with this argument, funds with the highest fire-sale exposure have abnormal 3-month fund returns that are on average 1% lower than funds in the lowest exposure quintile. Funds in the fifth exposure quintile also have on average 1.6% lower netflows than funds in the first exposure quintile. This suggests that fund investors reacted to the poor performance by withdrawing liquidity.

4.3.2 Multivariate results

To test whether our descriptive results hold in a multivariate framework, we estimate the relationship between fire-sale exposure, fund performance, and fund flows in several regressions. In all of these regressions, we control for common time trends by including time fixed effects and for unobserved heterogeneity across styles using style fixed effects. Similar to Coval and Stafford (2007), we also control for lagged performance and flow variables to ensure that our results are not driven by delayed investor reactions. We cluster standard errors at the fund level to account for non-independent observations within funds (Petersen, 2009) and report all regression results in Table 6.

*** Insert Table 6 about here ***

We first examine the link between fund performance and fire-sale exposure by regressing 3-month abnormal fund returns on the fire-sale (FS) exposure variable. As evident in column (1), there exists a negative relationship between exposure and fund performance. A one standard derivation increase in fire-sale exposure is associated with a decrease in fund performance of about 1.1% (in absolute terms).

In column (2), we examine how fund flows respond to fund performance in general by regressing the funds' quarterly performance on their netflows in the next quarter. Consistent with the literature, we find that future netflows tend to be low when fund performance is poor.

In columns (3) to (5), we investigate whether this flow-performance relationship still holds if the performance drop is a result of holding fire-sale stocks. Column (3) shows that fire-sale pressure is negatively correlated with future fund flows if we do not adequately control for fund performance in the current quarter. An increase in fire-sale exposure by one standard deviation, is associated with 0.6% higher outflows in the next quarter.

In column (4), we run the same regression, but control for fund performance in the fire-sale quarter. If the correlation between fire-sale exposure and flows is, as argued, driven by the flow-performance relationship and investors do not differentiate between the reasons for poor performance, the exposure coefficient should now become insignificant. As expected, we do not find any significant relationship between flows and the exposure variable once we adequately control for fund performance.

In column (5) we additionally interact fund performance with our fire-sale exposure variable. The interaction term turns out to be insignificant, while the flow-performance relationship continues to hold. Our results indicate that investors withdraw liquidity even if the poor performance results from price pressure induced by fire-sales.

4.3.3 Institutional vs. retail investors

Our finding that investors do not differentiate between the reasons for poor performance is perhaps somewhat surprising as the performance of funds with high fire-sale exposure should revert once fire-sale stocks start to recover. Hence, some sophisticated investors, such as institutional investors, might come to the conclusion not to withdraw liquidity. We analyze, therefore, whether retail and institutional investors react differently to performance losses that are linked to closed-end fund fire-sales. For that purpose, we calculate for each fund the aggregate flows to all of its institutional and, separately, all of its retail share classes. Hence, we end up with two share class observations for each fund. We then analyze whether institutional and retail fund flows of the same fund differ, when funds are exposed to fire-sales. To conduct this analysis, we estimate the following regression framework:

$$\begin{aligned}
SC\ Flows_{c,i,q+1} = {} & \beta_1 \cdot FS\ Exposure_{i,q} \cdot Retail_{c,q} \cdot Performance_{i,q} \\
& + \beta_2 \cdot Retail_{c,q} \cdot Performance_{i,q} \\
& + \beta_3 \cdot FS\ Exposure_{i,q} \cdot Retail_{c,q} \\
& + \beta_4 \cdot Retail_{c,q} + \gamma \cdot X_{cq} + \alpha_{i,q} + \epsilon_{c,i,q}
\end{aligned} \tag{6}$$

The variable $SC\ Flows_{c,i,q+1}$ denotes the flows to share class c of fund i at quarter $q+1$. $FS\ Exposure_{i,q}$ measures each fund's exposure to closed-end fund fire-sales. $Performance_{i,q}$ captures the 3-month abnormal performance of each fund. $Retail_{c,q}$ is a dummy variable that equals one if the share class is a retail class and zero if the share class is catered to institutional investors. Similar to the regressions above, we control for lagged netflows of each share class to account for potential long-term trends (X_{cq}). We include 'fund x time' fixed effects to only consider the variation between institutional and retail investors of the same fund at the same time. Note that all variables that do not vary at the share class level are absorbed by these fixed effects (e.g. $FS\ Exposure_{i,q} \cdot Performance_{i,q}$). We expect the β_1 coefficient to be positive, which would indicate that institutional investors withdraw less liquidity from a fund with poor performance and high exposure to fire-sales. If institutional investors, however, react differently to performance regardless of the level of exposure, we should only observe a significant β_2 coefficient.

*** Insert Table 7 about here ***

As evident in Table 7, we do not find evidence that institutional investors respond differently than retail investors to fund performance in general. The β_2 coefficient is insignificant in both columns regardless whether the triple interaction term is included or not. However, we find evidence that institutional investors react less strongly to past performance if the fire-sale exposure is high, supporting our hypothesis.

4.4 Fire-sale cascades

As shown in the previous section, open-end funds that are strongly invested in fire-sold stocks suffer from subsequent performance losses. This performance drop results in fund outflows. Coval and Stafford (2007) document that outflows can cause fire-sales. Therefore, we examine in this section whether the exposure to fire-sales results in sufficiently high outflows to induce a cascade of additional fire-sales by open-end funds.

We examine this question following a similar procedure as in Section 4.2.1, in which we studied the fire-sales of ARS-levered funds. Instead of using the selling pressure measure based on ARS-levered funds, however, we sort all stocks in five quintiles according to our cascade pressure measure, which we defined in Section 4.4. Cascade pressure measures the extent to which a stock is sold by all open-end funds, weighting the sale of each fund by its exposure to fire-sale stocks in the previous quarter. We exclude all stocks that are held by ARS-levered funds at the beginning of each quarter to isolate the price pressure induced by open-end funds from the price pressure created by ARS-levered funds.[25] Similar as before, we define each stock's event quarter as the quarter in which the cascade pressure is highest within the sample period and use the event study methodology of Kolari and Pynnönen (2010) to analyze abnormal stock returns.

*** Insert Figure 6 about here ***

Table 8 and Figure 6 show that stocks in the highest quintile have on average strong 4-factor abnormal returns of -6.4% in the event quarter. These stock returns are not only economically large, but also significant at the 1% level. Moreover, they are followed by a strong reversal over the following four months, which amounts to 7.4%.[26] This reversal is consistent with a temporary price drop due to fire-sales and rebuts other explanations such as a change in investors' expectations, which would require permanent price changes. Note that the event quarter in this table is not the quarter in which stocks by ARS-levered funds are fire-sold, but the quarter thereafter. This timing difference mitigates the concern that the observed price patterns are related to macro effects, general co-movements of portfolios, or general market trends. Overall, our findings suggest that a shock in the closed-end fund sector can transmit to stocks in the open-end fund industry. This highlights that markets are strongly interconnected and emphasizes the risk of financial contagion.

*** Insert Table 8 about here ***

[25] Our results are stronger if stocks held by ARS-levered funds are included.

[26] Note that we changed the table labels in comparison to the previous section slightly to document this effect.

While we do not find evidence for fire-sales in the lower quintiles consistent with our story, it should be noted that stocks in the second quintile experience on average a weaker but statistically significant price decrease. This price decreases is followed by significant reversals. We do not have an explanation at hand to explain these findings.

5 Robustness and further tests

5.1 Pseudo cascade pressure

To verify that the channel of contagion is linked to investors flows, we conduct a placebo test based on all *non-ARS levered* closed-end funds. For that propose, we construct a placebo cascade pressure for these funds. This measure is constructed similarly to the cascade pressure in the previous section, but relies on the aggregate sales by non-ARS levered funds.

$$FS\ exposure_{i,t}^{non-ARS} = \sum_{m=0}^{2} \sum_{j} Monthly\ selling\ pressure\ (TG)_{j,t-m} \cdot w_{i,j,t-3} \tag{7}$$

$$Cascade\,pressure_{j,t}^{non-ARS} = \sum_{i}^{non-ARS} \frac{max(-\Delta Shares_{i,j,t}, 0) \cdot FS\ exposure_{i,t-3}^{non-ARS}}{NOSH_{j,t}} \tag{8}$$

Due to their closed structure, closed-end funds are not subject to inflows or outflows. Consequently, non-ARS levered closed-end funds should not feel any pressure to fire-sale assets due to being exposed to initial fire-sales by ARS-levered funds. We, therefore, expect no price fluctuation in response to their asset sales.

As in the previous section, we use event studies to test whether stocks with high pseudo cascade pressure show abnormal fund returns. We exclude all stocks that were held by ARS-levered funds at the beginning of the quarter. We also exclude all stocks whose (true) cascade pressure belongs to the top quintile. This way we make sure that we do not pick up any price effect that arises due to fire-sales by other institutions.

As evident in Table 9, we do not find evidence for fire-sales using our pseudo cascade pressure measure. The abnormal returns of the considered stocks are statistically not differentiable from zero except for stocks whose pseudo cascade pressure belongs to the fourth quarter. Within this fourth quintile, however, the average abnormal return is positive. Thus, the sales by non-ARS levered funds, which are not subject to the flow-performance relationship, do not appear to have caused price pressure.

5.2 Robustness tests

We examine the robustness of our results by making several changes to our experimental design.[27] First, we follow Coval and Stafford (2007) and repeat our analysis using the following alternative measure for selling pressure:

$$Selling\,pressure(TG)^{alt}_{j,t} = \sum_{i}^{i \in ARS} \left(\frac{max(-\Delta Shares_{i,j,t}, 0)}{Avg.\ trading\ vol_{j,t-6;t-12}} \middle| Redemption_{i,t} = 1 \right) \tag{9}$$

We use this alternative measure to make sure that our results are not driven by the denominator (i.e. shares outstanding). Our results remain very similar with negative stock returns of about -8.2% in the selling quarter for the top selling pressure quintile, followed by significant reversals.

[27] All results are available upon request.

Second, we use alternative event study methodologies. While magnitudes are not affected by this robustness test, the statistical significance increases to the 1% level if we use the methodology proposed by MacKinlay (1997) or by Boehmer, Masumeci, and Poulsen (1991), which do not account for correlations across returns.

Third, instead of using 4-factor abnormal returns we analyze stock returns that are adjusted for only one (market factor) or five factors (Fama and French, momentum and the liquidity factor of Pastor and Stambaugh, 2003).[28] The fire-sale patterns are visible in all specifications, while magnitudes vary from -8.5% to -14% for the top selling pressure quintile.

Finally, as control group II differs in several dimension from the treatment group, we use propensity score matching techniques to select those non-ARS levered funds that compare best to the ARS-levered funds in our sample based on observables such as leverage and size. We do not find any evidence for fire-sales in this redefined control group II.

6 Conclusion

In this study, we use the failure of the auction rate security (ARS) market in February 2008 as a natural experiment to provide evidence for fire-sale cascades. We find that funds that redeem ARS finance these redemptions by selling assets. These sales are associated with negative 4-factor stock returns of up to -10%. Consistent with fire-sales and inconsistent with permanent price declines due to changes in the stocks' fundamentals, this price drop is followed by reversals in the following 12 months. We show that the price pressure effect induced by ARS-levered funds transmits to initially unaffected open-end funds that are invested in fire-sale stocks. When open-end fund

[28] We do not use the 5-factor model as our base specification since the liqudity factor is only available in a monthly frequency. Hence, we would need to estimate betas over a five year window.

investors observe the performance deterioration resulting from this investment in fire-sale stocks, they update negatively about the fund manager's ability and withdraw liquidity. This investor behavior is well known in the literature and it is also observable if the poor performance is a result of fire-sales. In response to these fund outflows, open-end funds are forced to liquidate assets themselves. We find that those sales show similar, but weaker fire-sale patterns. In the selling quarter stocks sold by pressurized open-end funds fall by up to -6.4%, even if we exclude all stocks held by ARS-levered funds at the beginning of the quarter. This price decline is only from temporary nature and reverses in the subsequent months. Our findings suggest that initial fire-sales can create sufficient price pressure to set off a cascade of additional fire-sale cascades posing a threat to financial stability.

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Appendix

A.1 Figures

Figure 1: Dividend yields around the failure of the ARS market

This figure shows the SIFMA Auction Rate 7-Day index, the 1-month treasury rate and the average (maximum) dividend yield of ARS issues in our sample around the ARS market failure in February 2008. The SIFMA Auction Rate 7-day index is based on self-reported (weekly changing) data from actual ARS issues provided by broker dealers and auction agents. The average maximum dividend yield is based on 38 ARS issues in our sample, for which data is available. All rates are scaled by the 1-week US LIBOR interest yield.

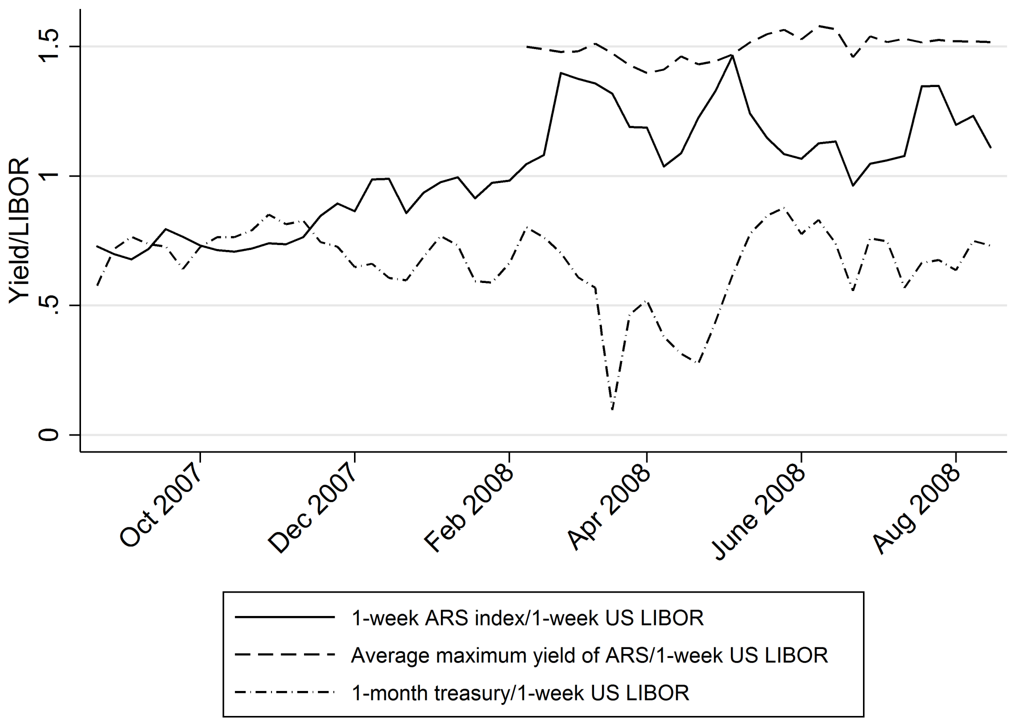


Figure 2: The volume of ARS and other liabilities

This figure shows the number of auction rate security (ARS) users as well as the total volume of outstanding ARS and other liabilities around the ARS market failure in February 2008. A fund is defined to be an ARS user if the fund reports ARS on its balance sheet in a given period. The figure is based on 53 funds that use ARS as part of their leverage strategy.

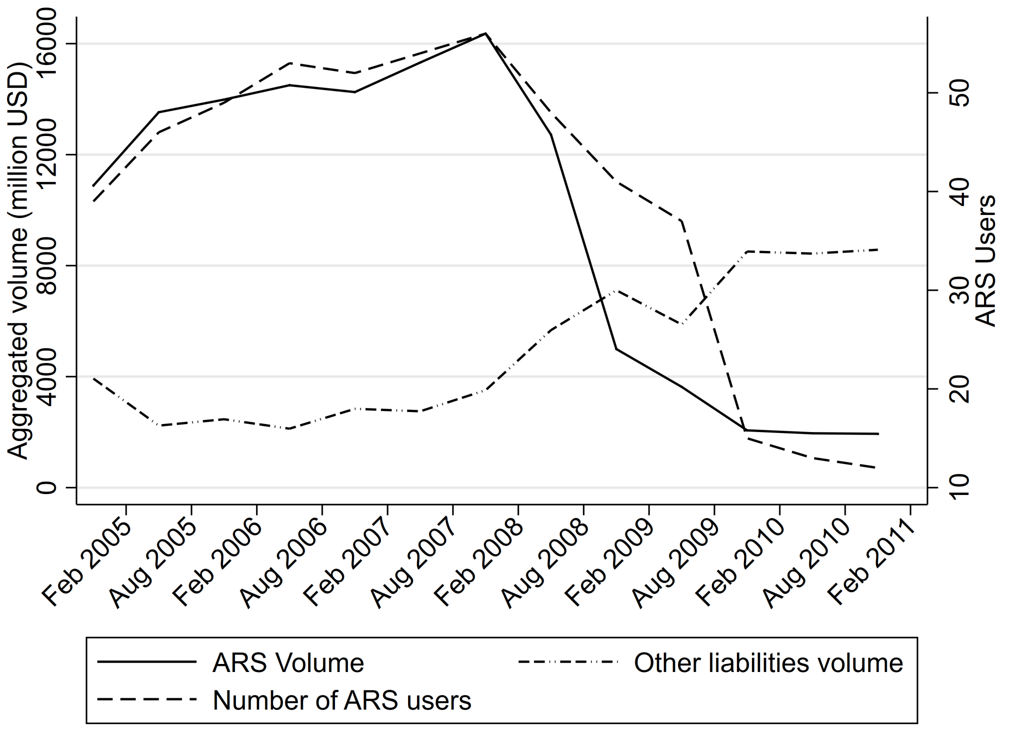


Figure 3: The distribution of fire-sales

This figure shows the distribution of stocks in the top selling pressure quintile of the treatment group (TG), control group I (CGI) and control group II (CGII). The TG (CGI) is based on sales by ARS-levered funds in (non-) redemption periods. CGII is based on sales by non-ARS levered funds. Selling pressure (TG), (CGI) and (CGII) measures the extent to which a stock is sold by the respective group. Each stock is counted at most once by only considering the quarter in which the stock has its highest selling pressure within the sample period from 2008 to 2010. The figure is based 169, 253 and 630 stocks in the top selling pressure quintile of the treatment, control group I and control group II, respectively.

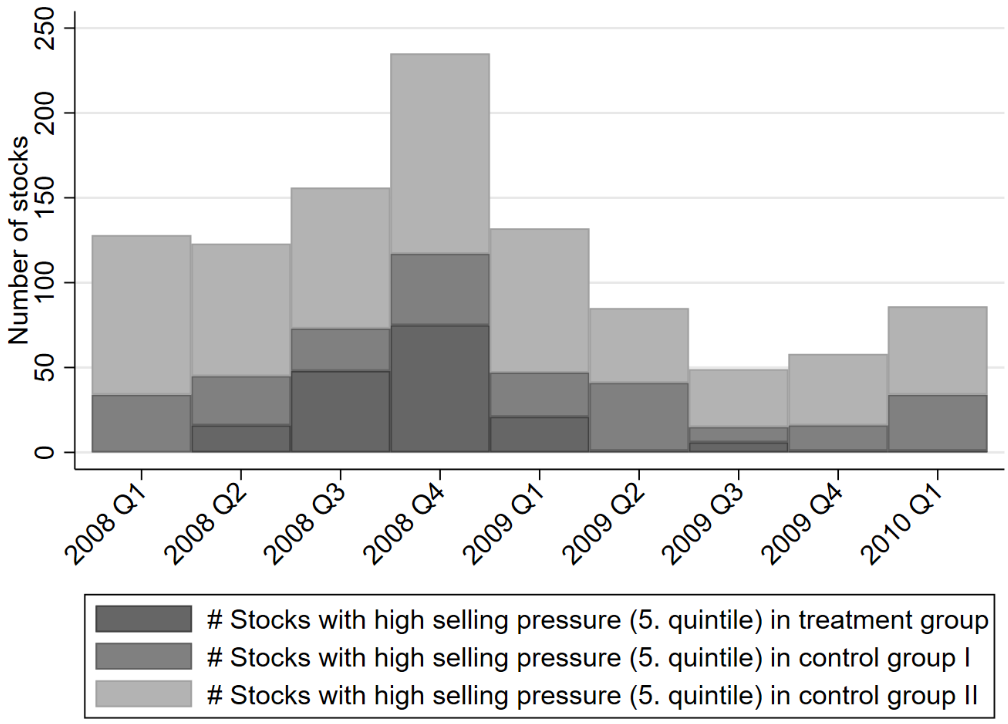


Figure 4: Selling pressure & stock returns

These figures show 4-factor cumulative abnormal returns for stocks in the top selling pressure quintile of the treatment group (TG), control group I (CGI) and control group II (CGII). The TG (CGI) is based on sales by ARS-levered funds in (non-) redemption periods. CG II is based on sales by non-ARS levered funds. Selling pressure (TG), (CGI) and (CGII) measures the extent to which a stock is sold by the respective group. The event quarter of a stock (E1, E2, E3) is the quarter in which its selling pressure is the highest within the sample period from 2008 to 2010. The cumulative returns are based on monthly returns around this quarter. All variables are defined in Appendix A.I.

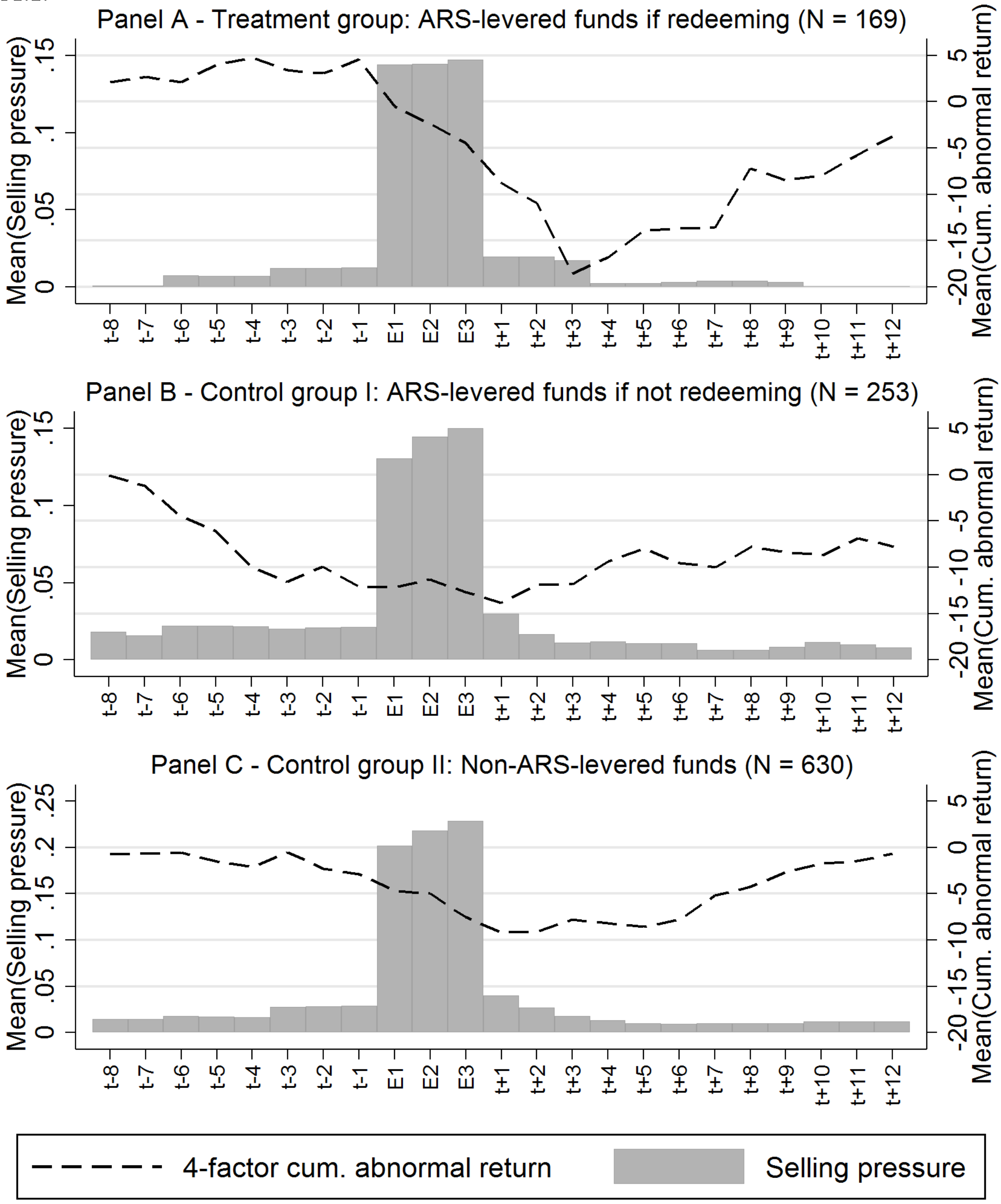


Figure 5: Selling pressure & short sales

These figures show 4-factor cumulative abnormal returns and the short sale volume for stocks in the top selling pressure quintile of the treatment group (TG), control group I (CGI) and control group II (CGII). The TG (CGI) is based on sales by ARS-levered funds in (non-) redemption periods. CGII is based on sales by non-ARS levered funds. Selling pressure (TG), (CGI) and (CGII) measures the extent to which a stock is sold by the respective group. The event quarter of a stock (E1, E2, E3) is the quarter in which its selling pressure is the highest within the sample period from 2008 to 2010. The cumulative returns are based on monthly returns around this quarter. All variables are defined in Appendix A.I.

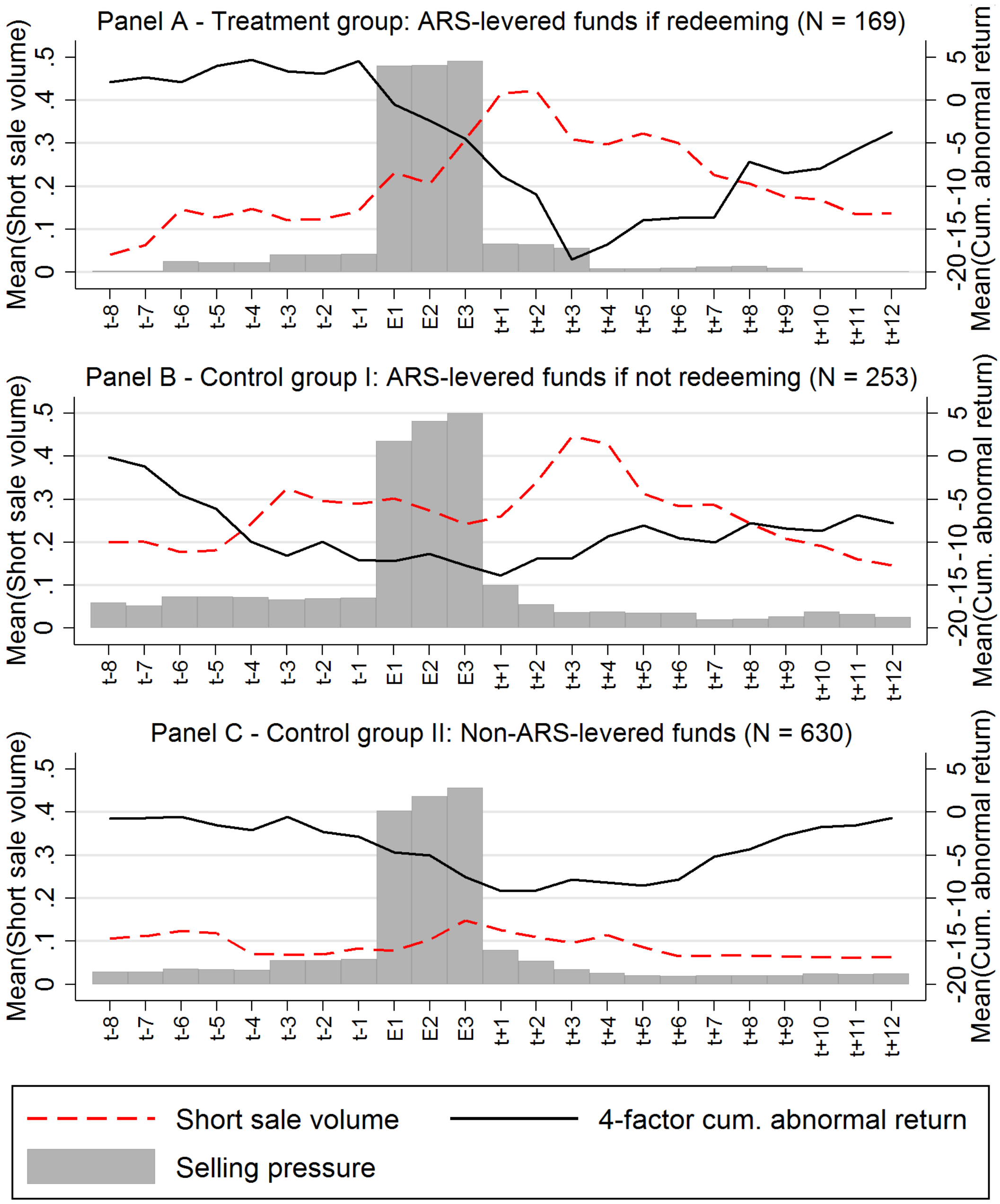
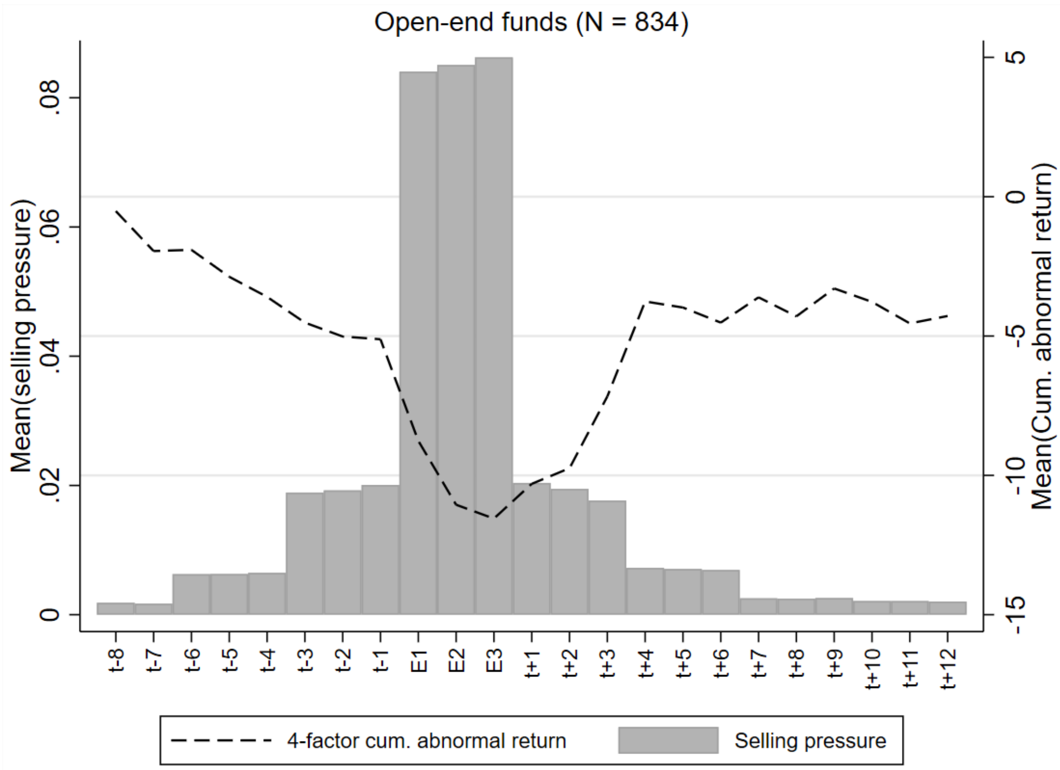


Figure 6: Cascade pressure & stock returns

This figure shows 4-factor cumulative abnormal returns for stocks in the top cascade pressure quintile. Cascade pressure is defined in Section 4.4 and captures the extent to which a stock is sold by all open-end funds weighted by each fund's exposure to fire-sales by ARS-levered funds in the previous quarter. The event quarter of a stock (E1, E2, E3) is the quarter in which its cascade pressure is the highest within the sample period from 2008 to 2010. The cumulative returns are based on monthly returns around this quarter. All variables are defined in Appendix A.I.



A.2 Tables

Table 1: Descriptive statistics: ARS-levered, non-ars levered and open-end funds

This table reports descriptive statistics for fund and holding characteristics of ARS-levered and non-ARS levered funds as well as open-end funds for December 2007. (Non-) ARS-levered funds are closed-end funds that (do not) have ARS on their balance sheets at the end of 2007. Panel A contains summary statistics on the fund level, while descriptives for fund stock holdings are reported in Panel B. Variables that are scaled by total net assets (TNA) are marked accordingly. All variables are defined in Appendix A.I.

	TG and CG I		**CG II**			
	ARS-levered (N = 53)		**Non-ARS-levered (N = 155)**		**Open-end (N = 1,469)**	
	Mean	p50	Mean	p50	Mean	p50
Panel A: Fund characteristics, December 2007						
Total assets (mio USD)	1,000	720	558	312	1,135	258
TNA (mio USD)	679	485	509	278	1,135	258
Turnover ratio (%)	21.85	17.60	42.13	27.03	84.53	62.00
Total leverage (% TNA)	50.96	53.80	9.12	2.24		
ARS leverage (% TNA)	44.87	46.51	0.00	0.00		
Other leverage (% TNA)	6.36	0.21	9.12	2.24		
Panel B: Stock holding characteristics, December 2007						
Avg. Market cap (bill USD)	28.407	19.321	26.440	18.376	26.762	23.309
Avg. Trading volume (bill USD)	216.281	168.069	221.920	194.013	237.824	210.549
Avg. Relative bid-ask (%)	0.169	0.158	0.202	0.131	0.139	0.121
Avg. Market beta	0.814	0.930	1.116	1.065	1.089	1.084

Table 2: Treatment and control groups

This table reports descriptive statistics from February 2008 to February 2010 for three groups: (i) ARS-levered funds in periods in which they redeem auction rate securities (ARS), (ii) ARS-levered funds in periods in which they do not redeem ARS and (iii) non-ARS levered funds over the entire sample period. (Non-) ARS-levered funds are closed-end funds that (do not) have ARS on their balance sheets at the end of 2007. Panel A displays the average change in total investments, total leverage and ARS leverage as a percentage of total investments of the previous quarter. Panel B shows average stock characteristics based on stocks that are sold or not sold by each of the above groups. All variables are defined in Appendix A.I.

Panel A: Total investments and leverage (means)

	Treatment group	**Control group I**	**Control group II**
	ARS-levered funds if redeeming	ARS-levered funds if not redeeming	Non-ARS-levered funds
Δ Total investments (% TI_{t-1})	-13.70	-3.88	-5.35
Δ Total leverage (% TI_{t-1})	-6.32	-1.10	-0.55
Δ ARS (% TI_{t-1})	-16.46	.	.

Panel B: Portfolio Characteristics (means)

	Treatment group		**Control group I**		**Control group II**	
	ARS-levered funds if redeeming		ARS-levered funds if not redeeming		Non-ARS-levered funds	
	Stocks sold	Stocks not sold	Stocks sold	Stocks not sold	Stocks sold	Stocks not sold
Market cap (bill USD)	18.692	19.043	18.760	20.560	22.139	19.417
Trading volume (bill USD)	218.056	218.565	245.106	238.186	265.112	222.292
Past monthly return (%)	-2.243	-0.903	-1.652	-0.741	-0.847	-1.105
Past stock volatility (%)	3.120	3.231	3.629	3.494	3.665	3.535
Past dividend yield (%)	3.134	2.609	2.825	3.087	2.169	2.090
Market beta	1.048	1.091	1.107	1.107	1.100	1.064
Relative bid-ask (%)	0.197	0.203	0.221	0.224	0.224	0.230

Table 3: Selling pressure and stock returns

This table shows 4-factor abnormal returns for stocks in the treatment group (TG), control group I (CGI) and control group II (CGII). The TG (CGI) is based on sales by ARS-levered funds in (non-) redemption periods. CGII is based on sales by non-ARS levered funds. Stocks are sorted into five quintiles according to each stock's highest selling pressure during the sample period. Selling pressure (TG), (CGI) and (CGII) measures the extent to which a stock is sold by the respective group. The event quarter of a stock is the quarter in which its selling pressure is the highest within the sample period from 2008 to 2010. All variables are defined in Appendix A.I. T-Values are reported in parentheses and are based on the event study methodology of Kolari and Pynnönen (2010). *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

Panel A - Treatment group: ARS-levered funds if redeeming (169 observations per quintile)

		4-factor abnormal returns					
	Selling pressure	Event	t;t+3	t+3;t+6	t+6;t+9	t+9;t+12	t+3;t+12
Quintile 1 (lowest)	0.001**	-1.785	-1.142	-1.572	0.618	-0.631	-1.577
		(-0.55)	(-0.73)	(-0.84)	(0.02)	(-0.40)	(-0.70)
Quintile 2	0.003**	-1.742	-4.324	0.369	2.927	0.711	3.940
		(-0.70)	(-1.58)	(0.24)	(0.63)	(0.16)	(0.38)
Quintile 3	0.008**	-9.321***	-2.679	-0.588	2.353	-0.189	1.552
		(-3.74)	(-1.20)	(-0.01)	(1.23)	(-0.02)	(0.64)
Quintile 4	0.025**	-10.410***	-5.307	4.085	8.457***	6.880***	19.097***
		(-3.19)	(-1.60)	(1.18)	(2.71)	(2.83)	(3.53)
Quintile 5 (highest)	0.147**	-9.062*	-13.670***	4.614	4.883	5.027	14.344*
		(-1.77)	(-2.95)	(0.87)	(1.35)	(1.55)	(1.78)

Panel B - Control group I: ARS-levered funds if not redeeming (253 observations per quintile)

	Selling pressure	Event	t;t+3	t+3;t+6	t+6;t+9	t+9;t+12	t+3;t+12
Quintile 1 (lowest)	0.001	-1.802	-0.739	-0.557	1.450*	0.435	1.278
		(-1.00)	(-0.92)	(-0.29)	(1.73)	(0.07)	(0.82)
Quintile 2	0.004	-1.609	-2.299	2.839*	1.411	-1.433	2.848
		(-1.53)	(-1.36)	(1.72)	(0.60)	(-1.30)	(0.58)
Quintile 3	0.011	-5.819***	-2.649	-2.059*	0.633	-0.040	-1.490
		(-3.40)	(-1.15)	(-1.83)	(0.10)	(-0.17)	(-1.16)
Quintile 4	0.029	-1.429	0.144	1.736	2.325	-1.708	2.381
		(-0.15)	(0.46)	(0.75)	(1.47)	(-0.65)	(0.94)
Quintile 5 (highest)	0.150	-0.611	0.294	3.098	0.972	-0.497	3.569
		(-0.44)	(0.53)	(1.62)	(0.81)	(-0.06)	(1.45)

Continued on next page

Table 3: continued from previous page

Panel C - Control group II: Non-ARS-levered funds (630 observations per quintile)

		4-factor abnormal returns					
	Selling pressure	Event	t;t+3	t+3;t+6	t+6;t+9	t+9;t+12	t+3;t+12
Quintile 1 (lowest)	0.003	-3.227**	1.741	0.439	-0.155	-2.965***	-2.533
		(-2.51)	(0.62)	(0.06)	(-0.21)	(-2.85)	(-1.24)
Quintile 2	0.013	-1.288	0.168	0.226	-0.242	-1.254	-1.232
		(-1.27)	(0.31)	(0.71)	(-0.20)	(-0.88)	(-0.21)
Quintile 3	0.031	-0.963	-1.761	-1.607	-1.157	0.559	-2.204
		(-0.95)	(-1.41)	(-1.12)	(-0.48)	(1.27)	(-0.21)
Quintile 4	0.068	-0.440	1.977	3.025**	1.126	2.826**	6.797**
		(-0.01)	(1.03)	(2.14)	(0.30)	(2.02)	(2.28)
Quintile 5 (highest)	0.228	-4.683***	-0.640	-0.814	2.264	2.452	3.608
		(-2.66)	(-0.37)	(-0.12)	(1.42)	(1.45)	(1.58)

Table 4: Predictability and stock characteristics of fire-sale stocks

This table report OLS and logit regressions to evaluate which factors determine high selling pressure. Selling pressure is defined in Section 2.1.3 and measures the extent to which a stock is sold by ARS-levered funds during redemption periods. The dependent variable is each stock's highest value of selling pressure during the sample period from 2008 to 2010, and expressed either as a continuous variable or as a dummy variable. The dummy variable equals one if a stock's maximum selling pressure belongs to the top quintile. The variable 'Total shares held by ARS-levered funds$_{2007}$' is defined for each stock as the aggregated sum of shares held by ARS-levered funds at the end of 2007, scaled by shares outstanding. All other variables are defined in Appendix A.I. Marginal effects are shown for regression (2) and are computed at mean values. Standard errors are heteroskedasticity robust. T-Values are reported in parentheses. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	Dependent variable	
	Selling pressure (TG)	
	Selling pressure (%)	5. Quintile (highest)
	(1)	(2)
Predictability		
Shares held by ARS-levered funds$_{2007}$ (%)	0.024***	0.695***
	(6.50)	(5.61)
Stock characteristics		
Log(Market cap)	-0.018***	-0.857***
	(-4.68)	(-4.72)
Market beta	-0.010	-0.229
	(-1.56)	(-0.93)
Liquidity beta	-0.036***	-1.376***
	(-3.13)	(-2.61)
Log(Trading Volume)	0.012***	0.595***
	(3.11)	(3.65)
Dividend yield (%)	0.004***	0.152***
	(4.21)	(4.05)
N	530	530
R^2	0.387	
Pseudo R^2		0.274
Marginal Effects	No	Yes
Positive predictive value (%)	-	68.63
Negative predictive value (%)	-	84.97
Correctly classified (%)	-	83.40

Table 5: Open-end fund exposure to fire-sales by ARS-levered funds

This table shows mean values of (i) the fire-sale (FS) exposure variable, (ii) the proportion of assets invested in stocks with different levels of selling pressure, (iii) the abnormal fund performance and (iv) the netflows in the subsequent quarter. The mean values are based on 1,469 open-end funds that are sorted into five quintiles according to their level of fire-sale exposure within the sample period from 2008 to 2010. Fire-sale exposure is defined in Section 2.2 and captures the extent to which an open-end fund is exposed to fire-sales by ARS-levered funds. Selling pressure is defined in Section 2.1.3 and measures the extent to which a stock is sold by ARS-levered funds during redemption periods. All other variables are defined in Appendix A.I.

		% invested in stocks with selling pressure...				
	FS exposure	in quintile 3	in quintile 4	in quintile 5	3m abn. return_q (%)	3m fund net flows_{q+1}
Quintile 1 (lowest)	0.0000	0.2411	0.0549	0.0027	-0.0008	1.0174
Quintile 2	0.0005	3.3475	0.9396	0.1285	-0.0030	0.1059
Quintile 3	0.0012	6.9155	2.8159	0.3870	-0.0056	0.3053
Quintile 4	0.0027	8.7719	6.2923	1.4392	0.0033	-0.4105
Quintile 5 (highest)	0.0099	6.1623	9.0567	8.2273	-0.0099	-0.6967

Table 6: Fire-sale exposure, fund performance and fund flows

In Column (1) we report a OLS regression relating the fire-sale exposure of open-end funds to 3-month abnormal fund returns. Columns (2) to (5) show regression estimations relating the fire-sale exposure to the funds' 3-month netflows experienced in the next quarter. Fire-sale (FS) exposure is defined in Section 2.2 and measures the extend to which an open-end fund is exposed to fire-sales by ARS-levered funds. The 3m abnormal return is the 3-month fund return in excess of the value weighted return of all open-end sample funds. All other variables are defined in Appendix A.I. The regressions are based on all open-end funds during the sample period from February 2008 to February 2010. T-Values are reported in parentheses. Standard errors are heteroskedasticity robust and clustered at the fund level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	3m abn ret$_q$	3m fund net flows$_{q+1}$			
	(1)	(2)	(3)	(4)	(5)
Main variables					
FS exposure (%)	-1.91***		-0.87***	-0.38	-0.62
	(-14.28)		(-2.68)	(-1.14)	(-1.16)
3m abn ret$_q$		0.35***		0.25***	0.27***
		(10.01)		(4.68)	(4.62)
FS exposure * 3m abn ret$_q$					-3.89
					(-0.53)
Lagged variables					
3m abn ret$_{q-1}$		0.13***	0.15***	0.15***	0.15***
		(4.13)	(3.28)	(3.38)	(3.39)
3m abn ret$_{q-2}$		0.15***	0.18***	0.20***	0.20***
		(3.48)	(2.96)	(3.22)	(3.16)
3m abn ret$_{q-3}$		0.08***	0.12**	0.12**	0.12**
		(2.61)	(2.42)	(2.56)	(2.56)
3m abn ret$_{q-4}$		-0.03	-0.04	-0.01	-0.02
		(-0.90)	(-0.72)	(-0.27)	(-0.30)
3m abn ret$_{q-5}$		0.04	0.04	0.06	0.05
		(1.14)	(0.78)	(1.20)	(1.19)
3m abn ret$_{q-6}$		0.01	-0.03	-0.03	-0.03
		(0.42)	(-0.49)	(-0.49)	(-0.47)
3m fund flows$_q$		0.13***	0.09**	0.08**	0.08**
		(5.24)	(2.37)	(2.18)	(2.18)
3m fund flows$_{q-1}$		0.10***	0.16***	0.16***	0.16***
		(5.40)	(4.19)	(4.19)	(4.18)
3m fund flows$_{q-2}$		0.05***	0.02	0.02	0.02
		(4.51)	(1.02)	(0.97)	(0.98)
3m fund flows$_{q-3}$		0.05***	0.06*	0.06*	0.06*
		(3.84)	(1.93)	(1.91)	(1.91)
3m fund flows$_{q-4}$		0.02	-0.01	-0.01	-0.01
		(1.61)	(-0.20)	(-0.23)	(-0.24)
3m fund flows$_{q-5}$		0.03*	0.02	0.02	0.02
		(1.93)	(0.76)	(0.77)	(0.78)
3m fund flows$_{q-6}$		0.03**	0.04	0.04	0.04
		(2.06)	(1.59)	(1.63)	(1.63)
N	7,106	19,301	6,285	6,285	6,285
Adjusted R^2	0.0798	0.100	0.0760	0.0811	0.0810
Style fixed effects	Yes	Yes	Yes	Yes	Yes
Quarter-time fixed effects	Yes	Yes	Yes	Yes	Yes

Table 7: Retail vs. Institutional fund flows

This table reports OLS regression results examining the relationship between fund performance, fire-sale exposure and netflows to institutional and retail share classes of open-end funds. For each fund, the 3-month netflows to all institutional and retail share classes are separately aggregated, such that for each fund only two share class observations remain. 3-month netflows for share class c (retail or institutional) and fund i are the sum of monthly net flows which are calculated using the following formula: Monthly net $\text{flows}_{c,t} = \text{TNA}_{c,t} - \text{TNA}_{c,t\text{-}1} \cdot (1 + \text{R}_{c,t})$. Fire-sale exposure is defined in Section 2.2 and measures the extent to which an open-end fund is exposed to fire-sales by ARS-levered funds. Retail is a dummy variable that equals one if the share class caters to retail investors, and zero otherwise. The 3m abnormal return is the 3-month fund return in excess of the value weighted return of all open-end sample funds. All other variables are defined in Appendix A.I. The regressions are based on share classes of all open-end funds during the sample period from February 2008 to February 2010. T-Values are reported in parentheses. Standard errors are heteroskedasticity robust and clustered at the share class level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	3m fund net flows_{q+1}	
	(1)	(2)
FS exposure * 3m abn fund ret_q * Retail		13.04**
		(2.03)
3m abn fund ret_q * Retail	-0.10	-0.16
	(-1.11)	(-1.37)
Retail (Y/N)	-0.03***	-0.04***
	(-6.71)	(-6.92)
FS exposure * Retail		1.52*
		(1.86)
N	6,648	6,648
Adjusted R^2	0.223	0.223
Fund x quarter time fixed effects	Yes	Yes
Lagged flows	No	No

Table 8: Cascade pressure and stock returns

This table shows 4-factor abnormal returns for stocks split into five quintiles according to the stocks' cascade pressure. Cascade pressure is defined in Section 4.4 and captures the extent to which a stock is sold by all open-end funds weighted by each fund's exposure to fire-sales by ARS-levered funds in the previous quarter. The event quarter of a stock is the quarter in which its cascade pressure is highest during the sample period from February 2008 and February 2010. All variables are defined in Appendix A.I. T-Values are reported in parentheses and are based on the event study methodology of Kolari and Pynnönen (2010). *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

Open-end funds: 834 observations per quintile

		4-factor abnormal returns						
	Cascade pressure	Event	t;t+1	t+1;t+2	t+2;t+3	t+3;t+4	t;t+4	t+4;t+12
Quintile 1 (lowest)	0.000	2.093	-0.025	0.476	-2.449***	0.121	-1.748	10.040***
		(1.09)	(-0.01)	(0.50)	(-2.70)	(0.60)	(-0.86)	(3.69)
Quintile 2	0.002	-3.648**	1.539	-0.866	1.650	3.200**	5.297*	7.721**
		(-2.16)	(0.81)	(-0.61)	(1.52)	(2.47)	(1.85)	(1.96)
Quintile 3	0.009	-2.002	2.100	-0.094	1.395	2.423*	5.681	2.138
		(-1.09)	(1.22)	(-0.42)	(0.95)	(1.82)	(1.48)	(0.38)
Quintile 4	0.028	-0.525	1.821	0.312	1.097	2.503	5.638	-1.793*
		(-0.17)	(1.02)	(0.23)	(0.48)	(1.39)	(1.39)	(-1.73)
Quintile 5 (highest)	0.086	-6.435***	1.306	0.757	2.244	3.238*	7.416*	-2.969
		(-2.75)	(0.77)	(0.62)	(1.31)	(1.84)	(1.92)	(-1.06)

Table 9: Placebo: Pseudo cascade pressure and stock returns

This table shows 4-factor abnormal returns for stocks split into five quintiles according to each stock's pseudo cascade pressure. Pseudo cascade pressure is defined in Section 5.1 and captures the extent to which a stock is sold by all non-ARS funds weighted by each fund's exposure to fire-sales by ARS-levered funds in the previous quarter. The event quarter of a stock is the quarter in which its pseudo cascade pressure is highest during the sample period from February 2008 and February 2010. All variables are defined in Appendix A.I. T-Values are reported in parentheses and are based on the event study methodology of Kolari and Pynnönen (2010). *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

Non-ARS levered funds: 218 observations per quintile

		4-factor abnormal returns						
	Cascade pressure	Event	t;t+1	t+1;t+2	t+2;t+3	t+3;t+4	t;t+4	t+4;t+12
Quintile 1 (lowest)	0.000	-1.725	1.764	-1.464	-0.034	0.961	1.212	-7.529***
		(-1.00)	(1.18)	(-1.26)	(-0.27)	(0.41)	(0.10)	(-3.16)
Quintile 2	0.000	1.309	1.365	0.506	3.068**	2.497**	7.320***	5.939
		(1.04)	(0.88)	(0.30)	(2.34)	(2.02)	(2.65)	(1.51)
Quintile 3	0.000	-1.737	0.449	1.327	1.810*	0.875	4.419	3.876
		(-0.31)	(0.10)	(0.57)	(1.75)	(0.26)	(0.98)	(1.35)
Quintile 4	0.000	5.284**	2.572*	2.615	3.576***	2.640**	11.355***	8.362**
		(2.03)	(1.72)	(1.38)	(3.76)	(2.16)	(4.02)	(2.48)
Quintile 5 (highest)	0.005	-4.426	0.027	-0.064	1.751	2.153	3.746	5.362**
		(-1.49)	(0.33)	(-0.11)	(1.38)	(1.45)	(1.21)	(2.09)

A.3 Variable definitions

Table A.I: Variable Definitions

Variable Name	Definition	Source
Leverage characteristics:		
ARS leverage	Liquidation value of all auction rate securities on the fund's balance sheet, scaled by TNA.	N-SAR, N-CSR, N-Q
Other leverage	The sum of all liabilities on the fund's balance sheet less the liquidation value of all auction rate securities, scaled by TNA.	N-SAR, N-CSR, N-Q
Total leverage	The sum of other and ARS leverage.	N-SAR, N-CSR, N-Q
Redemption	A dummy variable which equals one if the fund reports a decreases in its outstanding ARS by more than 1% in comparison to the previous quarter.	N-SAR, N-CSR, N-Q
Types of funds:		
ARS-levered fund	A closed-end fund that reports ARS leverage on its last available balance sheet before February 2008.	N-SAR, N-CSR, N-Q
Non-ARS-levered fund	A closed-end fund that reports no ARS leverage on its last available balance sheet before February 2008.	N-SAR, N-CSR, N-Q
Pressure measures:		
Selling pressure$(\text{TG}_{j,t}$	$\sum_i^{i\in\text{ARS}}\left(\frac{\max(-\Delta\text{Shares}_{i,j,t},0)}{\text{NOSH}_{j,t}}\middle\vert \text{Redemption}_{i,t}=1\right)$	
Selling pressure$(\text{CGI})_{j,t}$	$\sum_i^{i\in\text{ARS}}\left(\frac{\max(-\Delta\text{Shares}_{i,j,t},0)}{\text{NOSH}_{j,t}}\middle\vert \text{Redemption}_{i,t}=0\right)$	
Selling pressure$(\text{CGII})_{j,t}$	$\sum_i^{i\in\text{non-ARS}}\left(\frac{\max(-\Delta\text{Shares}_{i,j,t},0)}{\text{NOSH}_{j,t}}\right)$	
M. selling pressure$(\text{TG})_{j,t}$	$\sum_{m=0}^{2}\frac{1}{3}\cdot\text{Selling pressure}_{j,t+m}$	
FS exposure$_{i,t}$	$\sum_{m=0}^{2}\sum_j \text{M. selling pressure(TG)}_{j,t-m}\cdot\text{weight}_{i,j,t-3}$	
Cascade pressure$_{j,t}$	$\sum_i^{\text{i}\in\text{Open-end funds}}\frac{\max(-\Delta\text{Shares}_{i,j,t},0)\cdot\text{FS exposure}_{i,t-3}}{\text{NOSH}_{j,t}}$	
Fund characteristics:		
Turnover ratio	Min(purchases, sales)/average value of portfolio	N-SAR, CRSP
Monthly fund flows$_{i,t}$	$\text{TNA}_{i,t}-\text{TNA}_{i,t-1}\cdot(1+\text{Fund return}_{i,t})$	CRSP

Continued on next page

Table A.I: continued from previous page

Variable Name	Definition	Source
3-month abn. return	3-month fund return over the weighted return by all open-end funds in the sample.	CRSP
Stock characteristics:		
4-factor abnormal return$_{j,t}$	Stock return$_{j,t} - \sum_{k=1}^{4}$ factor return$_{k,t} * \beta_{j,k,t}$, where the factor returns are the (i) market, (ii) size, (iii) value-to-book, and (iv) momentum factors. The betas are estimated by regressing the stocks' excess daily returns on the factor returns over 250 trading days.	CRSP, Fama/French, Pastor
Liquidity beta	The regression coefficient of the Pastor liquidity factor when regressing the fund's monthly excess returns over the previous six years on the (i) excess market return, (ii) the Pastor liquidity factor, (iii) the size factor, (iv) the value-to-book factor, and (v) the momentum factor.	CRSP, Fama/French, Pastor

A.4 Event study methodology

The event study methodology used in this paper is adopted from a recent study by Kolari and Pynnönen (2010). Their design accounts for potential return autocorrelations and correlations across stock returns as well as event-induced increases in stock return volatility. The test statistics reported in all event-study tables are obtained in the following way:

1. For each stock j, we estimate betas by running the following time-series regression:

$$Stock\ return_{j,t} = \alpha_j + \sum_{k=1}^{4} Factor\ return_{k,t} * \beta_{j,k,t} + \epsilon_{jt} \tag{10}$$

   The regressions are based on daily returns in the estimation window $[t_0, t_1]$ that spans from February 2007 to January 2008. Factor loadings are only estimated if more than 40 stock observations are available during the estimation period. The factor returns are (i) the excess market return, (ii) the size factor, (iii) the value-to-book factor, and (iv) the momentum factor.

2. We use the factor loadings to calculate abnormal returns:

$$Abnormal\ return_{j,t} = Stock\ return_{j,t} - \hat{\alpha}_j - \sum_{k=1}^{4} Factor\ return_{k,t} * \hat{\beta}_{j,k,t}, \tag{11}$$

3. We obtain cumulative abnormal returns for event window $[t_2, t_3]$ by taking the sum of stock j's abnormal return in this window:

$$CAR[t_2, t_3]_j = \sum_{z=t2}^{t3} Abnormal\ return_{j,z} \tag{12}$$

4. We calculate standardized cumulative abnormal returns using the following formulas:

$$SCAR_j = \frac{CAR[t_2, t_3]_j}{s_j^{CAR}}, \tag{13}$$

$$s_j^{CAR} = \sqrt{s_j^2 \cdot \frac{T_{Event}^2}{T_{Estimation}} + \sum_{k=1}^{4} \frac{\sum_{y=t2}^{t3} (Factor\ return_{k,y} - \overline{Factor\ return}_k)^2}{\sum_{z=t0}^{t1} (Factor\ return_{k,z} - \overline{Factor\ return}_k)^2}}, \tag{14}$$

$$s_j = \frac{1}{T_{Estimation} - 1} \sum_{z=t0}^{t1} (Abnormal\ return_{j,z} - \overline{Abnormal\ return_j})^2, \qquad (15)$$

where T_{Event} and $T_{Estimation}$ denotes the number of observations in the event $[t_2, t_3]$ and estimation window $[t_0, t_1]$, respectively. $\overline{Factor\ return_k}$ and $\overline{Abnormal\ return_j}$ is the average (abnormal) return of factor k and stock j in the estimation period.

5. Using the $SCAR_j$ of all N event stocks, we construct the average standardized cumulative abnormal return in the event window:

$$ASCAR = \frac{1}{N} \sum^{N} SCAR_j \qquad (16)$$

6. We calculate the Boehmer, Musumeci,and Poulsen(1991) t-test by dividing the $ASCAR$ by its cross-sectional standard deviation:

$$T_{BMP} = \sqrt{N} \frac{ASCAR}{s^{CAR}} \qquad (17)$$

$$s^{CAR} = \sqrt{\frac{1}{N-1} \cdot \sum^{N} (SCAR_j - ASCAR)^2} \qquad (18)$$

7. To account for cross-sectional correlation of abnormal returns, we finally adjust this test-statistic using the average cross-correlation of abnormal returns ($\bar{r}$) across all event stocks in the estimation period:

$$T_{KP} = T_{BMP} \sqrt{\frac{1 - \bar{r}}{1 + (N-1)\bar{r}}}, \qquad (19)$$

$$\bar{r} = \frac{1}{N(N-1)} \sum_{k=1}^{q} N_k (N_k - 1) \bar{r}_k, \qquad (20)$$

where N_k event stocks with the same event date are assigned to group k and $\bar{r}_k$ denotes the cross-correlation of abnormal returns of these stocks in the estimation period.

Securities Lending and Fund Risk: Evidence from Mutual Bond Funds

Laurenz Klipper

Abstract:

We examine whether mutual bond funds increase their risk exposure through securities lending transactions by reinvesting the cash collateral of these transactions in risky assets. Consistent with such risky collateral reinvestments, we find that the return volatility of government bond funds increases with the percentage of securities on loan. This relation is only evident among funds whose lending agent likely reinvests the lending collateral riskily. Fund risk is unrelated to lending if the lending program is managed by an agent who typically relies on non-cash collateral which cannot be reinvested. In contrast to government bond funds, corporate bond funds do not exhibit a similar risk-lending link.

Keywords: Mutual funds, risk, securities lending

JEL-Classification: G11, G18, G23, G31

1 Introduction

"Pressure to improve returns could spur undue risk taking whether via direct credit exposure or through securities lending and cash reinvestment."
— International Monetary Fund (2015)

Securities lending by mutual funds is commonly perceived as a risk-free way to generate additional income for fund investors. However, the lending activity of mutual funds can lead to an increase in risk exposure since most lending transactions are collateralized by cash, which can be reinvested by the lender.[1] Those reinvestments work like leverage because the lender is exposed to both price changes of the reinvested collateral and of the securities lent. Current fund regulation leaves sufficient room for a collateral reinvestment with substantial risk exposure. The Securities and Exchange Commission (SEC) only vaguely mandates that collateral needs to be invested in short-term and "sufficiently liquid" instruments. While the leverage and risks embedded in securities lending programs are not necessarily detrimental for fund investors, several regulators including the SEC, the International Monetary Fund (IMF), and the Financial Stability Board (FSB) recently expressed their concerns about the opacity of reinvestment practices by mutual funds, which makes it "impossible to understand fully the extent and nature of financial risks to investors in the funds and to markets".[2] The objective of this study is to shed light on these risks by systematically analyzing the relationship between lending and fund risk in a large sample of mutual bond funds.

Studying the impact of lending on fund risk is challenging because neither the funds' lending activity nor their collateral reinvestment is directly observ-

[1] Securities lending transactions that are collateralized by cash account for about 70% to 85% of all lending transactions.

[2] Quotation taken from a report of the International Monetary Fund (2015). See the reports of the International Monetary Fund (2015) and the Financial Stability Board (2012) for a summary of how securities lending is perceived by regulators worldwide.

able. The main contribution of our study is to address these challenges. While we are unable to obtain information on collateral reinvestments, we proxy for the funds' lending activity by collecting data on the collateral received for securities on loan.[3] Using this data we are able to measure the lending volume for a sample of 887 government bond funds and 834 corporate bond funds over a time period that spans from 1996 to 2011.

However, this information alone does not allow for a thorough risk-lending examination as any observed correlation between risk and lending might be driven by unobserved factors that affect both lending and fund risk. Acknowledging this problem, we employ two identification strategies that both rely on additional data on the funds' lending agents.[4] The lending agent is the institution that runs the securities lending program on behalf of the fund.[5] In our first set of analyses, we identify funds whose lending agent is not a traditional bank but a central depository (about 12% of all cases). In programs managed by central depositories, the lender typically does not receive cash collateral for loaned securities, but relies on assets of the borrower pledged by the depository as a guarantee. Hence, funds whose lending agents are central depositories do not have the possibility of risk-taking through (cash) collateral reinvestments.

While the data on central depositories is helpful for the identification of funds whose lending transactions are collaterized by non-cash securities, it does not allow for a differentiation between funds that reinvest their cash collateral in risk-free assets and those that reinvest their collateral in risky assets. For that reason, we consider a second identification strategy that is

[3] As we do not observe individual liability positions, we take the liability volume of all liabilities contained in the N-SAR category 'other liabilities' to proxy for the funds' lending collateral. In a random sample of 100 bond funds, the lending collateral accounted for 80% of this category.

[4] We identify lending agents using data about each fund's custodian bank, which typically coincides with the lending agent.

[5] A few large funds manage their lending program on their own without relying on a lending agent.

more noisy but targets the set of funds that are more likely to reinvest their cash collateral riskily. We target those funds by assuming that a lending agent runs a riskier reinvestment program if the financial press reported about lending losses generated by the agent during the sample period. This is a clear indicator that at some point the agent's collateral pool was invested in risky assets.[6] As a lending agent manages the lending programs of multiple clients, the lending loss of an agent is not necessarily generated on behalf of our sample funds. However, some risk commonality in the reinvestment strategy across an agent's collateral pools seems plausible; for example, because some agents rely more strongly on cash collateral than others.[7]

In support of the idea that lending impacts fund risk, we find that there exists a positive risk-lending relationship among government bond funds who do not employ a central depository as their lending agent. Similarly, we find that this relation is more pronounced if the fund's lending agent has run risky reinvestment programs at least once during the sample period. These results are obtained after controlling for fund and time fixed effects that account for potential time trends and time-invariant heterogeneity across funds.

The relationship is also economically sizable. A one standard deviation increase in the lending collateral of government bond funds is associated with an increase of the median return volatility (idiosyncratic risk level) by 2% to 3% (4% to 6%). This magnitude is a result of pooling all funds whose agents are non-depositories (identification I) or classified to be 'risky' (identification II). Since it is likely that among these groups not all funds follow risky reinvestment strategies, the documented risk-lending sensitivity is plausibly a lower bound and larger for some of the sample funds.

[6] In 54% of the observations, the respective lending agent realized lending losses at least once during the sample period.

[7] Since our identification is based on reinvestment outcomes, agents that did not realize losses could potentially have made reinvestments with similar or even more risk. However, the probability of realizing losses should increase with the risk embedded in the lending program, especially since most risky assets lost sharply in value during the financial crisis.

While using a fund's lending agent is an important part of our identification strategy, the choice of the lending agent is endogenous. We try to mitigate this concern by fixing the fund-agent relationship at each fund's first observation in our sample, at which the fund has not yet established a lending program.[8] Although the agent selection in earlier time periods bears similar endogeneity issues, it is clearly less likely that this selection is related to future lending and risk-taking. Moreover, the test makes sure that our results are not driven by a simultaneous change of risk and the lending agent. Using the fixed fund-agent relationship, we rerun all tests and show that the results are robust to this adjustment.[9]

Interestingly, we do not find a similar risk-lending relationship among the sample of corporate bond funds. The difference in the risk-lending sensitivity between corporate and government bond funds even persists if we only consider the variation across corporate and government bond funds within the same fund family or the same lending agent. These findings are consistent with the observation of the Federal Reserve (2013) that loans of government bonds involve greater embedded reinvestment risk than loans of corporate bonds.[10]

Overall, our results should be important for regulators, who currently try to asses the risks embedded in securities lending programs. Moreover, our findings should alert fund investors to carefully monitor the lending programs of their funds, especially given the large lending losses that some lenders experienced during the 2007-2009 financial crisis.[11]

[8] We eliminate all funds that had already a securities lending program in place at the fund's first year of appearance.

[9] We also run several other robustness tests described in Section 7.3.

[10] The Federal Reserve (2013) does not offer an explanation for this finding.

[11] The most prominent lending loss is the \$13 billion write-off by AIG that was caused by collateral reinvestments in mortgage backed securities. This and other losses are covered by a large number of financial articles including Weiss, Miles, "AIG to Absorb \$5 Billion Loss on Securities Lending", Bloomberg News (June 27, 2008); Karmin, Craig and Leslie Scism, "Securities-Lending Sector Feels Credit-Crisis Squeeze", Wall Street Journal (October 30, 2008); Story, Louise, "Banks Shared Clients' Profits, but Not Losses", The New York Times (October 18, 2010).

Apart from documenting a relationship between lending and fund risk, we also examine how many and what kind of bond funds lend securities. We find that the number of lending funds and the extent of lending has increased dramatically over the sample period. While at the beginning of the sample period in 1996, only about 7.5% of all government and corporate bond funds were engaged in securities lending, it was practiced by about 40% at the end of 2007 and by about 25% by 2011. Similarly, the average lending collateral of those funds engaged in securities lending increased from less than 4% of TNA to up to 12% from 1996 to 2011.

Lending is correlated with several fund characteristics. Older and retail oriented funds are more likely to lend out securities. Similar to equity funds (see Rizova, 2012; Evans, Ferreira, and Prado, 2016), the decision to lend out securities is positively related to fund size suggesting that economies of scale are an important factor. Confirming the results of Evans et al. (2016), we find that netflows are negatively correlated with fund lending. In the government bond fund sector, lending is more likely if fund turnover is high and past performance was poor. In contrast to the prediction of Porras Prado, Saffi, and Sturgess (2016), but consistent with collateral being invested in short-term securities, we show that the fraction of short-term assets in the portfolio of a fund is positively related to initiating a lending program.

Finally, we briefly analyze whether lending is associated with fund performance. Similar to the analysis before, we differentiate by the funds' lending agent, but do not find a relation between lending and fund performance for any agent type. This suggests that risk-taking in lending programs does not significantly impact fund performance.[12]

[12] We find, however, that restricted government bond funds perform better. This contrasts the results by Evans et al. (2016), who show that restricted equity funds have a lower fund performance.

Our results contribute to several strands of the literature. First, it is closely related to the literature that investigates the impact of lending on fund returns. Adams, Mansi, and Nishikawa (2014) show that lending returns of index funds that use sponsor-affiliated lending agents are substantially lower compared to the lending returns of funds with non-affiliated lending agents. These results suggest that securities lending programs are prone to agency problems. Evans et al. (2016) focus on active equity funds and document that funds which are engaged in securities lending experience lower fund returns, especially if funds face stronger investment restrictions. We contribute by showing that lending is also related to fund risk, which has not been documented before. Moreover, we show that lending is not negatively related to fund performance in the bond fund industry, even if bond funds are restricted.

Second, we contribute to the literature that examines the motives and determinants of mutual fund lending. Aggarwal, Saffi, and Sturgess (2015) show that one reason for securities lending is the transfer of voting rights prior to voting dates. Evidence presented in our paper suggests that risk-taking might be another motive for lending, beyond the desire to earn additional income. Rizova (2012) and Evans et al. (2016) investigate the determinants of lending of index and equity funds, respectively. We complement these studies by exploring a new data set of a large sample of U.S. mutual bond funds.

Lastly, our study is linked to the large body of literature (e.g. Brown, Harlow, and Starks 1996, Chevalier and Ellison 1997, Huang, Sialm, and Zhang 2011 and Goetzmann, Ingersoll, Spiegel, and Welch 2007) that documents that mutual funds strategically vary their risk levels. Fund risk can be altered using various instruments. For example, Chernenko and Sunderam (2014) show that money market mutual funds increase their risk exposure by lending to Eurozone banks. The findings of Koski and Pontiff (1999) and Adam and Guettler (2015) suggest that funds use derivatives to manage their risk levels in response to inflows and outflows or in crisis periods. Studying closed-end funds, Elton, Gruber, Blake, and Shachar (2013) find a correlation between leverage and fund return volatility. The evidence provided in this paper suggests that securities lending is used as an additional instrument for risk-taking.

The remainder of this paper is structured as follows. Section 2 provides institutional details. In Section 3, we discuss our empirical strategy. Section 4 covers the data. In Section 5, we describe the lending behavior of mutual bond funds using descriptive statistics. Section 6 reports our main empirical results. In Section 7, we present additional tests. Section 8 concludes.

2 Institutional background

In a typical transaction (illustrated in Figure 1), the beneficial owner of a security, such as a mutual fund, pension fund, or an insurance company, agrees to lend its securities to a borrower, usually a hedge fund or a brokerage firm, who provides cash or securities as collateral. The SEC requires the collateral value to be marked to market daily and to be at least 100% of the value of the lent securities. However, 102% collateral for domestic and 105% for non-US securities are industry standards. In the U.S., cash is by far the most common type of collateral and was used in about 83% (72%) of all lending transactions in 2009 (2011).[13] The vast majority of securities lending agreements are rolled over daily until the security is returned by the borrower or recalled by the lender, which is possible at any time. For the duration of the loan, ownership of the security is transferred to the borrower but the security remains effectively in the lender's portfolio as the lender retains the right to collecting all coupon payments and distributions of the lent securities.[14] Similar to the stock market, the most common reason for borrowing bonds (especially corporate bonds) is

[13] Federal Reserve (2013).

[14] For accounting purposes, the lent securities remain on the asset side of the balance sheet and the additional collateral leads to an expansion of the balance sheet.

to facilitate short sales. Bonds are, however, also borrowed for interest rate or capital spread arbitrage as well as for hedging, cost-effective collateralization, or making the market.

*** Insert Figure 1 about here ***

Mutual bond funds are allowed to lend bonds as long as a fund's securities on loan do not exceed 33.33% of its total assets. The securities lending programs of most mutual funds are run by an external lending agent, usually the funds' custodian, who provides the technology and expertise to aggregate market supply and manage the collateral process.[15] The agent also manage the counterparty risk by providing indemnification for all losses in case of a borrower's default. For their services, lending agents are compensated by taking a share of the lending income and in rare cases by charging a fixed service fee.[16] In transactions that are collalaterized by non-cash securities, a lending program generates income by charging a fee to the borrower. In cash collateral transactions, the income from securities lending is equal to the fee paid by the borrower plus the return earned on reinvesting the cash collateral.[17] The cash reinvestment rate depends on how the cash collateral is reinvested. The regulatory guidelines for collateral reinvestment are vague since securities lending programs by mutual funds are predominantly regulated through several no-action letters released by the SEC. While the SEC mandates in one of these letters that cash collateral reinvestment should be limited to short-term and sufficiently liquid instruments, it does not further specify what short-term and sufficiently liquid means and leaves the type of reinvestment largely to

[15] Due to the scale of investment required to set up a securities lending program, only some large funds manage their lending program on their own.

[16] According to the International Securities Lending Association (2015), the agent receives about 30% of the lending income on average.

[17] Technically, the lender does not receive a direct fee from the borrower, but generates income that equals to the cash reinvestment rate less a rebate rate. The rebate rate is typically below the overnight money market rate and is the rate that lenders have to channel back to the borrower for earning interest on the received cash collateral.

the fund directors' discretion. This leaves funds a large set of reinvestment choices.

3 Empirical methodology

The main objective of our study is to examine whether mutual funds use securities lending programs for risk-taking. Risk-taking in lending programs can be achieved by reinvesting the lending collateral in risky assets. Since collateral reinvestment decisions of funds are not observable, we study this question by analyzing the link between lending and total fund risk. This indirect examination is problematic as lending and fund risk are potentially affected by other variables. Therefore, observing a simultaneous increase in risk and lending does not necessarily imply that lending collateral is reinvested riskily.

Acknowledging this problem, we do not study the risk-lending correlation unconditionally, but distinguish between funds with different lending programs. A lending program can be organized in three different ways. First, lending transactions might be collateralized by non-cash securities. In this case collateral reinvestments are impossible. Second, lending funds might receive cash in exchange for lending securities, but decide to reinvest this collateral in risk-free assets. In both cases, the lending activity of a fund should not have any effect on fund risk. Finally, funds might receive cash collateral and reinvest it in risky securities. Given that the reinvestment and the lent securities both contribute to fund returns, the reinvestment is essentially a form of leverage, which will, ceteris paribus, increase fund risk.[18]

[18] Note that a risky reinvestment will only have a positive effect on fund risk if the collateral is reinvested in securities that show a non-negative correlation with the other investments of the fund (i.e. no hedging). Otherwise, lending would have a negative effect on fund risk. This can easily be seen when considering the variance of a portfolio that consists of reinvested collateral (marked by subscript '1') and other investments (subscript '2'): $Var(P) = w_1^2 \cdot var(r_1) + w_2^2 \cdot var(r_2) + 2w_1w_2 \cdot cov(r_1, r_2)$. Since a reinvestment in securities with negative correlation would work against us, such a behavior is unproblematic for our study.

*** Insert Figure 2 about here ***

While mutual funds do not disclose how their lending program is organized, we categorize funds by using information on the fund's lending agents. Lending agents are engaged by funds to manage their lending programs. We start by differentiating between funds whose lending agent is a traditional bank and funds whose program is managed by a central depository (identification I). Securities lending programs run by central securities depositories are special in the sense that the lender of a security usually does not receive cash collateral from the borrower. Instead, if needed, the lender can fall back on the securities of the borrower, for which the depository guarantees.[19] As illustrated in Figure 2, we use this information to identify funds whose lending transaction are collateralized by non-cash securities and contrast this group with all other funds. Given that the majority of U.S. lending transactions are collaterized by cash, the non-depository group should mainly consist of funds that receive cash collateral in exchange for lent securities. This gives rise to the following hypothesis:

Hypothesis 1 (Central depositories)

When a fund increases its securities lending activity that is managed by a central depository, the riskiness of fund returns increases to a smaller extent compared to programs that are run by other lending agents.

Using central depositories is useful to identify lending programs in which transactions are not collateralized by cash. However, it is less helpful in distinguishing between collateral reinvestments in risky and non-risky securities. For that reason, we use an alternative method that is more noisy, but identifies funds whose collateral is more likely reinvested in risky securities (identification II). The identification relies again on information about the funds' lending

[19] See the International Securities Lending Association (2015)'s report on securities lending for a short discussion about central securities depositories.

agent. We define a lending agent to be ‘risky’ if the financial press reported about lending losses that the agent generated on behalf of its clients during the sample period. Given that clients are typically indemnified against counterparty losses, these losses must have resulted from risky collateral reinvestments. As a lending agent makes individual arrangement with each client, risk-taking in some accounts does not necessarily imply that the reinvestment of all other accounts of the agent are equally risky. However, it is likely that the reinvestment strategy of an agent is correlated across its accounts, for example, because some agents rely more strongly on cash collateral than others. Hence, we expect agents that suffered from lending losses to have a higher probability of running a risky collateral reinvestment strategy. We compare funds with risky agents with funds whose lending programs are managed by non-risky agents (see Figure 2) and hypothesize:

Hypothesis 2 (Risky agents)
When a fund increases its securities lending activity that is managed by a risky agent, the riskiness of fund returns increases to a greater extent compared to programs that are run by other lending agents.

Note that our definition of risky agents is based on realized outcomes. Thus, we are only able to capture funds for which the collateral reinvestment resulted in losses. Other agents might have used similar or even riskier reinvestment strategies, which were just more successful. Hence, our defined group of non-risky agents could potentially include agents that take on similar or more risk through collateral reinvestments than the group of risky agents. This would impede the validity of our tests. However, most lending losses occurred in the financial crisis, in which almost all, especially the more volatile assets lost sharply in value. Thus, it seems plausible that the probability of a loss realization is an increasing function of risk embedded in lending programs.

4 Data

4.1 Data sources and sample

We use web-crawling techniques to obtain balance sheet data and other information on mutual funds' trading activities from SEC N-SAR forms, which U.S. investment companies are required to file twice a year. We clean the data by dropping all observations for which the fund name, TNA, or total assets are missing, negative, or zero. We eliminate entries for which the sum of all active balance sheet items does not equal the sum of all items on the passive side of the balance sheet. Using fund tickers or, if not available, fund names we match our data to the Center for Research in Security Prices (CRSP) Mutual Fund database. To avoid spurious mismatches, we inspect all matches manually and require net assets by both data sources to deviate by less than 5%.[20] To address the incubation bias identified by Elton, Gruber, and Blake (2001) and Evans (2010), we exclude all observations of a fund whose total net assets are smaller than $5 million in the previous month and whose reporting date is prior to the fund's inception date provided by CRSP. To eliminate closed-end funds we only keep funds that indicate to be an open-end investment company (N-SAR question 27). Records with a missing answer to question 27 are kept as long as total netflows over the past six months are nonzero.

To identify bond funds, we use question 62 on the N-SAR form, the proportion of assets invested in debt securities reported on the funds' balance sheets (N-SAR question 74), and the Thomson investment objective code (IOC), which we obtained by matching our data to Thomson Reuters using MFLINKS. A fund is classified as a bond fund if its IOC is either 5 (Municipal Bonds) or 6 (Bond & Preferred) and the fund indicated to be primarily

[20] We tolerate small deviations to allow for differences in net assets due to rounding and non-availability of small share classes in the CRSP database.

invested in debt securities (N-SAR question 62). If the IOC is not available or unclassified (IOC 9) the fund needs to have at least 80% of its assets invested in debt securities to be categorized as a bond fund. We exclude money market funds, which are identified by having turnover ratios of zero and non-missing daily net asset values on their N-SAR forms. We remove all funds that CRSP identifies as index funds or that report to be an index fund on their N-SAR forms (question 69). We also drop all funds that have more than 50% of their assets invested in state and municipal bonds as municipal bond fund typically do not engage in securities lending. Finally, we use the proportion of assets invested in corporate and government bonds to classify the remaining funds as corporate or government bond funds. While a corporate bond funds needs to have at least 50% of its assets invested in corporate bonds, a government bond fund needs to allocate at least 50% of its assets in U.S. treasuries or U.S. government agency bonds. We differentiate between securities lenders and non-lenders using N-SAR question 70 N. Our final sample, which spans from 1996 to 2011, consists of 8,569 observations by 887 distinct government bond funds and 7,215 observations by 834 distinct corporate bond funds.

Most of our variables are constructed using the data obtained from CRSP and SEC N-SAR forms as described in Appendix A.I. For calculating betas and alphas we additionally rely on the Barclays U.S. Aggregate Bond Index, Barclays U.S. Government Intermediate Index, Barclays U.S. Corporate High Yield Index, Barclays GNMA Index, and the stock market index, which we downloaded from Datastream and Kenneth R. French's website.

4.2 Measuring securities lending collateral

A key challenge of our study is to measure the extent to which funds are engaged in securities lending. As securities lending arrangements are bilateral and take place OTC, lending transactions are not directly observable. However, funds must disclose the cash or non-cash collateral they receive in exchange for lent securities as liabilities on their balance sheet. While we do not have data on single liabilities, we make use of information in SEC N-SAR forms, in which aggregated data for seven liability categories are contained. These categories are shown in Panel A of Table 1 for all funds that have lent securities over the past six months. The biggest liability category, which is responsible for about 52% of total liabilities, are payables that emerge from instrument purchases that are not yet settled. Liabilities that emerge from owing to affiliates, senior long term debt, reverse repurchase agreements, short selling, or written options are comparably small and represent in aggregate less than 4% of total liabilities. The low level of liabilities in these categories is consistent with Almazan, Brown, Carlson, and Chapman (2004), who show that the majority of open-end funds do not borrow, short sell nor trade with options. The lending collateral is contained in the category 'other liabilities', which accounts for about 45% of total liabilities ($77 million).

*** Insert Table 1 about here ***

To ensure that the category 'other liabilities' incorporates mainly lending collateral, we decompose this category for a random sample of 100 funds that were engaged in securities lending over the last six month and for which other liabilities exceeded 10% of their TNA. As shown in Panel B, the lending collateral is responsible for about 80% of the total volume of other liabilities. In comparison, payables and borrowings, which are the second and third strongest contributors to other liabilities, represent only 9% and 6%, respectively.[21] We use total other liabilities and the information whether a fund currently lends securities to proxy for each fund's lending collateral in the following way:

[21] In robustness tests we show that our results do not change if we exclude funds that indicated to borrow money (N-SAR question 70 O).

$$Securities\ lending\ collateral = \begin{cases} 80\% \cdot Other\ liabilities & , if\ lending \\ 0 & , otherwise \end{cases} \quad (1)$$

4.3 Identifying central securities depositories

Since lending programs are usually managed by the funds' custodian banks, we collect for each fund the name of its primary custodian using N-SAR question 15.[22] We use this data to construct the dummy 'Depository (Y/N)' that equals one if a fund declares that its custodian falls under Rule 17f-2 and, hence, classifies as a central securities depository (12% of all observations). Our dummy is set equal to zero if the custodian type is a bank (83%), foreign custodian (4%), or belongs to another category (1%).

4.4 Identifying risky agents

We classify lending agents as 'risky agents' on the basis of recent articles in the financial press. We carefully inspect news articles from the Financial Times, the New York Times, and the World Street Journal to identify securities lending agents whose collateral pools suffered losses during the sample period. Since counterparty risk is usually borne by the agent, the losses must have resulted from the reinvestment of cash collateral. Using this information, we create the dummy 'risky agent', which we set to one if the financial press mentioned the lending agent in connection with securities lending losses. For 54% of our observations this dummy equals one (risky), while for 46% the dummy equals zero.

[22] A few funds have more than one custodian bank. For these funds, we use the first custodian mentioned on the funds' N-SAR form.

5 Securities lending by mutual bond funds

5.1 Summary statistics

Table 2 shows summary statistics for securities lenders and non-lenders. All continuous variables are winsorized at the 1% levels. Panel A shows that government bond funds in our sample are considerably large. Government bond funds that lend securities have on average more assets under management ($0.9 billion) and are more frequently part of a fund family (80%) when compared to government bond funds that have no securities on loan ($0.7 billion and 76%). This suggests that economies of scale play an important role for setting up a lending program. Government bond funds that are engaged in lending report on average lending collateral on their balance sheets that represents 9.8% of the funds' total net assets. The high standard deviation as well as the low median value, however, indicate that some funds lend a much higher percentage of their assets. When compared to government bond funds that are not engaged in securities lending, lenders tend to be older (15 years compared to 13 years), have higher turnover ratios (209% compared to 188%), and attract less netflows from investors. Perhaps surprisingly, government bond funds that lend securities have slighlty lower 6-month 4-factor alphas (-1.3% compared to -1%) although lending programs offer an additional way to generate income. Lenders and non-lenders also show small differences, when we compare the restrictions on fund management (Almazan index) and the funds lending agents. Lending agents are differentiated either by distinguishing between central depositories and other lending agents or by classifying agents in 'risky' and 'non-risky agents'. In spite of these differences, lenders and non-lenders in the government bond sector are similar with regard to other dimensions. Both groups cater mainly to retail investors, have similar proportions invested in short-term securities, and show comparable risk characteristics. Interestingly, securities lenders and non-lenders also have similar expense ratios, which suggests that lending income is not used to lower management fees.

*** Insert Table 2 about here ***

Panel B reports the same descriptive statistics for corporate bond funds. Similar to government bond funds, lending funds in the corporate bond sector are larger ($1.1 billion in contrast to $0.8 billion), are more often part of a fund family (84% vs. 81%), are older (14 years vs. 12 years), receive lower netflows, and face lower management restrictions on average. The average lending collateral of corporate bond funds engaged in securities lending represents 6.9% of the funds' TNA. Hence, corporate bond funds lend out a smaller proportions of their portfolios on average, compared to government bond funds. While securities lenders perform more poorly in the government bond sector, they perform better within the corporate bond sector. There are no strong differences between lenders and non-lenders with regard to risk measures, the retail dummy, the expense ratio, the family dummy, and the portion invested in short term securities. As in the government bond sample, corporate funds that lend out securities, however, tend to employ central depositories and 'risky agents' slightly more frequently.

5.2 Securities lending over time

As illustrated in Figure 3, the aggregate volume of funds' lending collateral has increased strongly over the past years. At the beginning of the sample period in 1996, the total collateral volume amounted to less than $2.5 billion for government as well as corporate bond funds. By early 2008, the lending collateral of the government bond funds in our sample has increased to $40 billion while the lending collateral of all corporate bond funds was worth $13 billion in aggregate. Beginning in 2008, both fund classes reduced their lending activity slightly. At the end of our sample period in 2011, the lending collateral reached \$30 billion in the government and \$20 billion in the corporate bond fund sector. These levels represent significant portions of the entire securities lending market. For example, according to the Federal Reserve (2013) about 337 billion of government bonds were on loan in the U.S. by September 2011, which implies that collateral of our government bond fund sample was responsible for about 9% of the entire lending supply. The corporate bond funds in our sample contributed with a share of 13% to 26% (across time) even stronger to the market of corporate bond loans.[23]

*** Insert Figure 3 about here ***

The increase in securities lending volume could result from an increased number of securities lenders or an elevated portfolio proportion lent out by the same lending funds. To differentiate between these two possibilities and to better understand how many of our sample funds participated in lending transactions, Figure 4 shows the number of funds as well as the average lending collateral for our sample funds over time. Similar to the aggregated collateral volume, the number of securities lenders as well as the average collateral value of the lending funds shows a strong increase from 1996 to 2008. While in 1996 less than 10% (5%) of government (corporate) bond funds were engaged in securities lending, the lending proportion increased to about 35% (28%) in 2008. In the same period the average collateral value rose from 5% (2%) to 14% (10%) among our government (corporate) bond funds, which implies that the observed aggregate volume increase was a result of an increase in both the intensive and extensive margin. From 2008 to 2010, we observe a drop in the fraction of funds with lending programs as well as in the average lending collateral. However, at the end of the sample period in 2011, lending was still highly popular and used by 23% of all government bond funds and 24% of all corporate bond funds with an average lending collateral of about 8%.

[23] The Federal Reserve (2013) estimated an average volume of \$75 billion in the period between 2009 and 2012.

*** Insert Figure 4 about here ***

5.3 Securities lending and fund characteristics

Table 3 shows results of multinomial logistic regressions for our government and corporate bond funds. In these regressions we relate several fund characteristics to two dummy variables. The dummy variable used in columns (1) and (3) is called 'Lender' and equals one if the fund is currently engaged in securities lending. Since some funds have only very small proportions of their securities on loan, we use an alternative dummy as the dependent variable in the remaining regressions. This dummy equals one if funds have a lending collateral that exceeds 5% of their TNA ('Collateral > 5%').[24] We cluster standard errors at the fund level to account for non-independent observations within funds (Petersen, 2009) and use time fixed effects to absorb common time trends.

*** Insert Table 3 about here ***

Consistent with Rizova (2012) and Evans et al. (2016), who study the lending decision of equity and index funds, we find that fund size is positively and significantly correlated with our lending dummies in all four specifications. Given the potentially high costs of setting up a securities lending program, this relationship may be related to economies of scale considerations. Consistent with this argument, we also observe a significant correlation between lending and fund family membership. However, this correlation is only present among government bond funds and is unrelated to the 'Collateral > 5%' dummy. Older government and corporate bond funds are more likely to start lending, but age is only correlated with a lending volume of more than 5% in the government bond fund sector. Similar to Evans et al. (2016), we find that netflows

[24] Our results are largely similar if we use a 10% cutoff instead.

of the previous six months are negatively correlated to lending, except in column (2). The p-value of the netflow coefficient in this specification, however, is close to the 10% significance level. If the observed correlation between netflows and lending is a result of a causal relationship, it is unclear whether investors shy away from securities lending programs or managers start to increase their lending engagement in response to fund outflows. Government bond funds with a high turnover ratio lend securities more often and on a larger scale. Interestingly, we do not find a similar lending-turnover link for corporate bond funds. The expense ratio is not related to lending decisions. This is surprising as many funds claim that the lending income is used to reduce management fees. Government and corporate funds that are targeted to retail investors are more likely to initiate a securities lending program, but do not lend out more than 5% of their assets more frequently. Porras Prado et al. (2016) argue that funds that invest in long term securities are more likely to be a loan supplier of securities because their portfolios change less frequently. In contrast to their results, we find that funds who invest more in short term securities are more likely to lend securities in all specifications. This inconsistency is explainable by the fact that our sample funds are usually long-term investors with less than 7% of their assets invested in short term securities on average. Hence, the observed positive relationship might just result from funds investing part of their collateral in short-term securities. Finally, we find that government and corporate bond funds respond differently to past performance. Government bond funds increase their lending activity if alphas are low consistent with seeking additional sources of income after performing poorly (e.g. Brown et al. 1996 and Chevalier and Ellison 1997). Among corporate bond funds, we observe the opposite relationship if we consider the 'Lender' dummy, and no correlation if we consider the 'Collateral > 5%' dummy variable.

6 Securities lending and fund Risk

6.1 Central depositories vs. other lending agents

As described in Section 3, mutual funds employ different lending agents to run their lending programs. If the lending program is managed by a central depository, the typical lending transaction is not collateralized by cash, but is secured by the borrowers' assets pledged by the depository. For that reason, there is no opportunity for risky collateral reinvestments. We, therefore, estimate different risk-lending sensitivities for lending programs managed by depositories and other agents. For this estimation, we use the following regression framework:

$$Risk_{i,t} = \alpha_i + \alpha_t + \beta_1 \cdot Collateral_{i,t} \times CD_{i,t} + \beta_2 \cdot Collateral_{i,t} + \beta_3 \cdot CD_{i,t} + \gamma \cdot X_{i,t} + \epsilon_{i,t} \tag{2}$$

$Risk_{i,t}$ represents one of the following risk measures, which we will use as dependent variables in different regression specifications: (i) the standard deviation of fund returns, (ii) the beta measuring the sensitivity of fund returns to the U.S. aggregate bond index and (iii) the idiosyncratic risk, which is the residual variance not captured by the beta. We compute all risk measures over a six month window around the reporting date of the lending collateral.[25] $Collateral_{i,t}$ is the securities lending collateral of fund i at half-year t scaled by the fund's total net assets. $CD_{i,t}$ is a dummy variable that equals one if the fund's lending agent (proxied by the fund's custodian bank) is a central depository. Interacting the collateral with the central depository dummy allows us to obtain different coefficients for both agent types. We include time fixed

[25] While the collateral information we use is only a snapshot at the end of the reporting period, unreported analyses reveal that lending collateral volumes are highly persistent.

effects to capture potential time trends, such as general increases in return volatility or lending collateral. We use fund fixed effects to control for time-invariant differences between our sample funds. We also include time-varying fund characteristics ($X_{i,t}$) such as fund size, lagged fund performance, and turnover, which could potentially be correlated with fund risk and the lending collateral. Standard errors are clustered at the fund level and are, hence, robust to non-independent observations within funds.

*** Insert Table 4 about here ***

Table 4 reports the regression results for government (columns (1) to (3)) and corporate bond funds (columns (4) to (6)) separately to account for potential structural differences in their securities lending programs. In the government bond fund regressions, the interaction term is significantly and negatively correlated with the standard deviation and idiosyncratic risk of fund returns. In contrast, the coefficient of the non-interacted collateral is positive. The absolute magnitude of the interacted and non-interacted coefficient is statistically not differentiable. Hence, the risk-lending relationship is only observable for funds with non-depository agents, supporting *Hypothesis 1*. If a fund with a non-depository agent increases its lending collateral by one standard deviation, the return volatility (idiosyncratic risk) shows a simultaneous increase of 0.5% (0.4%) which represents about 2% (4%) of the mean value. As we use fund fixed effects in our regressions, this effect is not driven by time-invariant differences in our sample funds. In the beta specification, the interaction term as well as the non-interacted lending collateral is not significant. The observed risk increase, hence, is predominantly driven by risk exposure to a factor that is not systematically related to the aggregate bond index.

Turning to the corporate bond funds, the coefficients of the interaction term point in the right direction, but are not statistically differentiable from zero. One exception is the coefficient of the interaction term in regression (5), in which, however, the non-interacted coefficient is insignificant. Overall, the results do not suggest that there is a sizable correlation between lending and fund risk among corporate bond funds. We will discuss this result more thoroughly in Section 7.1.

6.2 Risky vs non-risky lending agents

In the previous section, we compared funds whose lending transactions are collateralized by non-cash securities with funds who are more likely to rely on cash collateral. The disadvantage of this comparison is that we do not directly identify funds that reinvest the collateral in risky assets. Moreover, funds using central depositories might be structurally different to funds that engage other agents. We, therefore, use an alternative method to classify lending agents with the intention to target funds that reinvest the collateral in risky securities. For that purpose we try to differentiate between 'risky' and other agents. As described in Section 3, we define an agent to be a 'risky agent' if there is evidence of the agent suffering lending losses during the sample period.[26] These losses indicate that the agent reinvested some of its collateral in risky securities. While the losses of the agent might not be generated on behalf of our sample funds, we assume that there is some risk commonality in the reinvestment strategy across the collateral pools of an agent. As in the previous section, we interact the lending collateral with the 'risky agent' dummy and hypothesize that funds with 'risky' agents show stronger risk-lending sensitivities (*Hypothesis 2*).

*** Insert Table 5 about here ***

[26] In Section 3 we discuss potential concerns of using realized outcomes to define our agents.

In the regressions reported in Table 5, we find support for our hypothesis among the government bond funds. The regression coefficient of the lending collateral is only significant if interacted with the 'risky agent' dummy. For funds with risky agents, a change in lending collateral by one standard deviation is associated with a 0.75% (0.5%) change in the funds' standard deviation (idiosyncratic risk measure) representing about 3% (6%) of the median value. For funds with non-risk agents, there is no lending-risk link consistent with the idea that on average these funds did not reinvest their lending collateral in (sufficiently) risky securities.

For corporate bond funds, we do not find any significant relationship between a fund's lending activity and risk, except in the idiosyncratic risk regression. In this regression the interaction term is significant at the 10% level, but is not statistically distinguishable from zero if taken in conjecture with the coefficient of the non-interacted lending collateral.

Overall, the results in the government bond fund sector imply that the risk-lending correlation varies with the type of the agent regardless whether we differentiate between central depositories and conventional banks or between risky and non-risky agents. All findings are in support of our story that some lenders reinvest their lending collateral in risky assets. Moreover, alternative stories are only plausible if they can explain the variation of the risk-lending sensitivities found across funds. For example, while it is likely that in times of high volatility short-sale demand and return risk is high, it is difficult to imagine why this should only affect funds with 'risky' agents.

6.3 Lending agents and endogeneity

While using lending agents helps to improve our identification, it raises a potential concern given that the choice of the agent is endogenous. For example, funds that run risky reinvestment strategies during periods, in which the demand for securities loans is high, might prefer a certain agent at this time. We try to mitigate this concern by fixing the fund-agent relationship using details on each fund's first observation in our sample. If a fund was already engaged in securities lending at the fund's first or second observation, we exclude the fund from the analysis.[27] Hence, all funds left in our sample have at least one year at the beginning of the sample period, at which they were not yet engaged in securities lending. For our test to work, we have to rely on two assumptions: First, the relationship between a bank and its clients needs to be persistent over time, an assumption supported by several papers in the relationship-banking literature. This literature argues that switching cost become more expensive the longer the relationship lasts (e.g. see Sharpe 1990 and Rajan 1992). Moreover, in our sample 58% of the funds employ the same agent over the whole sample period. Second, the choice of the lending agent at the beginning of the period should not be correlated with future return risk and future lending behavior. While we cannot rule out that such a correlation exists, we believe that endogeneity concerns are significantly mitigated by using fund information before the fund's first lending engagement. Having fixed the agent-lending relationship, we rerun our regressions of the previous sections and report the regression results for the government bond funds in Table 6.[28]

*** Insert Table 6 about here ***

Not surprisingly, fixing the agent-fund relationship reduces the power of our tests. However, in the regressions in which the standard deviation is the dependent variable, the coefficient of the interaction term remains statistically significant for both the central depository and the 'risky agent' regressions,

[27] Our results are stronger if we keep the entire sample. To be conservative, we exclude both the fund's first and second observation because the agent selection might have already occurred at the end of the previous period.

[28] To save space we omit results for the corporate bond fund sample.

which is consistent with our previous findings. If we regress our variables on idiosyncratic risk, the significance of the interaction term drops barely below the 10% level (t-value of -1.59) in the depository specification, but remains significant in in the risky agent regression (t-value of 1.89). Hence, the lending-risk correlation is generally robust to fixing the fund-agent relation.

7 Additional tests

7.1 Government vs. corporate bond funds

In the previous sections, we document a correlation between lending and fund risk for government bond funds, but do not find a similar relationship for corporate bond funds. We employ two additional tests to analyze this difference in greater detail. We start by documenting the differential effect between the two groups using a pooled regression. For that purpose we interact the lending collateral with a dummy variable that equals one if the fund is a government bond fund. Columns (1) to (3) of Table 7 document the results, which are in line with our previous findings. While we do not find any significance for the non-interacted lending collateral, the lending collateral interacted with the government bond fund dummy is positive and significantly related to the standard deviation of returns and the idiosyncratic risk measure.[29]

*** Insert Table 7 about here ***

Given our previous results, the difference between corporate and government bond funds might result from different fund-agent relationships. For example, the lending agents of corporate bond fund might have relied more strongly on non-cash collateral in general compared to government bond funds.

[29] In unreported tests, we also examine the difference between government and corporate bond funds when we differentiate by lending agents. Regardless of the lending agent, government bond funds have a higher risk-lending sensitivity compared to corporate bond funds.

We examine the role of the agent in columns (4) to (6) by including 'agent x time' fixed effects.[30] These fixed effects absorb all common variation that comes from an specific agent in a given time period. Hence, if the observed lending-risk heterogeneity between both fund groups is driven by some general characteristic or actions of a specific agent (e.g. a certain way the agent reinvests all of its collateral pools), the differential effect should vanish once we include agent-time fixed effects. However, as evident in Table 7, the difference in the collateral-risk correlation between the two fund groups still prevails.

In the last three columns, we examine whether the difference between corporate and government bond fund disappears if we compare funds of the same fund management company. For that purpose, we exclude all funds that do not belong to a fund family. We also drop a fund observation if in the considered period the fund management company does not own at least one government and corporate bond fund in our sample. We then include, similar as in the agent regressions, 'family x time' fixed effects to examine the variation within the same family in the same period. A drop in significance of the interaction term would imply that the difference between corporate and government bond funds is driven by funds belonging to different fund families that might have heterogeneous lending policies. Inconsistent with this explanation, the coefficient of the interaction term remains significant after including 'family x time' fixed effects.

Overall, our results indicate that the difference between government and corporate bond funds is not driven by a commonality on the agent or fund family level. Instead our results suggest that lending programs in the government and corporate bond market are structurally different. These findings are consistent with a recent report of the Federal Reserve (2013), which documents that the income of loaning government bonds depends more strongly

[30] Similar results are obtained by only including agent fixed effects.

on collateral reinvestments (and less strongly on lending fees) than the income of loaning corporate bonds.

7.2 Securities lending and fund performance

In this section, we examine the relationship between lending and fund performance as several studies suggest that lending affects performance. To measure fund performance, we calculate 4-factor alphas. Hence, lending can only impact fund performance if it generates returns that are not systematically related to the following risk factors: (i) the excess return of the US aggregated bond index, (ii) the excess return of the stock market, (iii) a default factor, and (iv) a mortgage market factor.[31] Similar to the previous sections, we differentiate between different lending agents using interaction terms. We additionally include a variable called 'Almazan index', which was introduced by Almazan et al. (2004) and is used by Evans et al. (2016) to measure whether fund managers are constrained.[32] In their sample of equity funds, Evans et al. (2016) find the lending activity of constrained funds to be negatively related to performance. We follow Evans et al. (2016) and interact this variable with the funds' lending activity.[33] We regress all interaction terms on fund performance and report the results in Table 8.

*** Insert Table 8 about here ***

Columns (1) to (3) show the regression estimates for the government bond fund sample, while regressions (4) to (6) are based on our corporate bond funds. In all specifications, the coefficient of the non-interacted lending collateral is insignificant. Similarly, we do not find any correlation between lending

[31] Our results are similar if we use 1-factor alphas which are only based on the US aggregated bond index. See Appendix A.I for a detailed description of how alphas are calculated.

[32] As described in Appendix A.I, we make small adjustments to the index to fit our bond fund sample.

[33] Note that Evans et al. (2016) do not use the lending collateral to measure the funds' lending activity. Instead, they rely on a dummy variable that equals one if the fund is engaged in lending and zero otherwise.

and performance if we interact the collateral with our agent dummies. This suggests that risk-taking through lending transactions is not per se detrimental to fund performance.

Interestingly, in the government bond fund regressions, (1) and (2), the interaction term that links the collateral and the Almazan Index is positive and significant. Such a relation is not observable among corporate bond funds. Both results are in contrast to the study of Evans et al. (2016), which implies that their findings are not transferable to the bond fund industry.

7.3 Robustness tests

We examine the sensitivity of our results using additional robustness tests.[34] First, since our measure of lending collateral might be contaminated by other forms of leverage we rerun our tests using only funds that indicate not to borrow money (N-SAR question 70 O). Second, we try to mitigate reverse causality concerns. Instead of relying on the six months around the fund's reporting date, we compute our risk over the next three months. Third, we examine whether our results are affected if we include all funds that never lend their securities. We use the custodian bank of these funds as their fictious agents. Our results are quantitatively and statistically robust to all of these adjustments.

8 Conclusion

The percentage of mutual bond funds that run securities lending programs has increased strongly over the past 20 years. While in 1996 less than 8% of the funds were engaged in securities lending, this percentage increased to almost 40% just before the outbreak of the financial crisis in 2007, falling back to 25% by the end of our sample period in 2011. During this time

[34] Results are available upon request.

period larger, older, and more retail oriented funds as well as funds with a higher proportion of assets invested in short-term securities were more likely to initiate a securities lending program. Lending transactions are also more frequently undertaken by government bond funds with high turnover and poor past performance. Despite the common perception that this activity is a riskless way of earning additional income, securities lending can be used to increase a fund's exposure to risk by reinvesting the collateral received in risky assets. Consistent with funds using their lending programs in this way, we find that the amount of securities on loan is positively associated with the return volatility of government bond funds whose lending transactions are likely collateralized by cash. In contrast, securities lending and fund risk is uncorrelated if the lending program is run by a central depository, in which the typical form of collateral are non-cash securities. We also document that the lending-risk relationship is more pronounced for government bond funds if there is evidence in the financial press that the lending agent generated lending losses during the sample period. These findings suggest that investors should take into account the potential risk embedded in securities lending programs and carefully monitor the lending strategy and activity of their funds. However, fund risk does not vary with lending for all of our sample funds. Interestingly, there is no risk-lending link among corporate bond funds. This difference between government and corporate bond funds even persists if we focus on corporate and government bond funds of the same fund family or the same lending agent. Exploring this difference further is an interesting task left for future research.

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Appendix

A.1 Figures

Figure 1: Securities lending transaction

This figure illustrates the mechanism of a typical securities lending transaction, in which loaned securities are collateralized by cash.

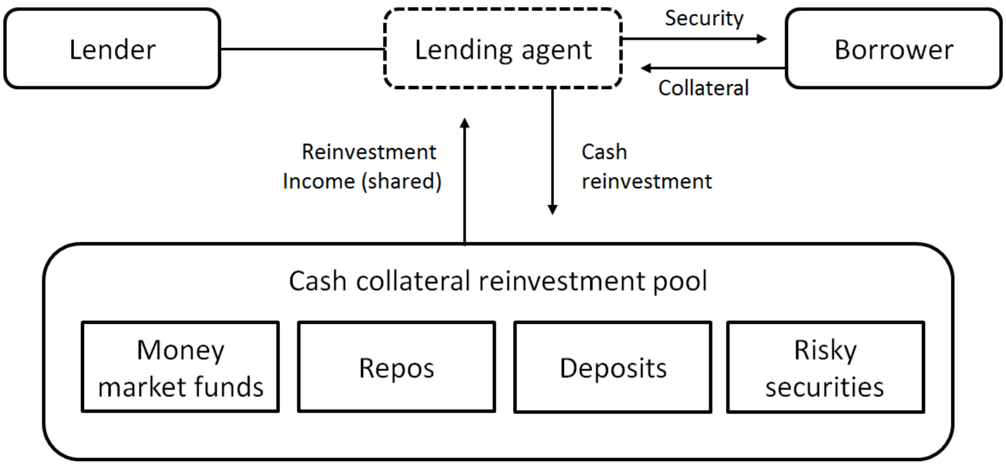


Figure 2: Identification

This figure illustrates how the lending agent of a fund is used to distinguish between different lending programs. While lending programs managed by central depositories are typically collateralized by non-cash securities, 'risky' agents are expected to rely more strongly on cash collateral and risky reinvestment strategies. Both agents are defined in Section 4.

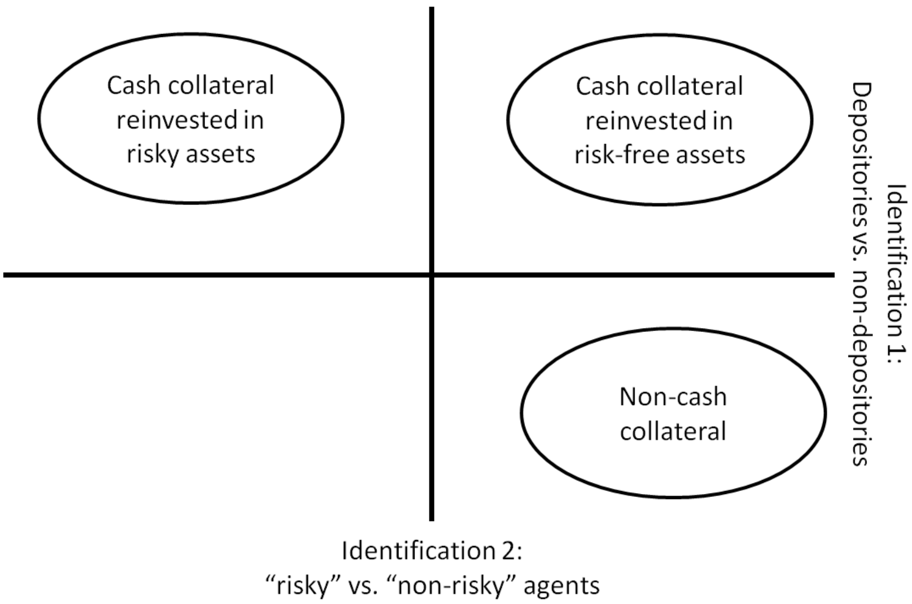


Figure 3: The volume of securities lending collateral

This figure displays the total aggregated volume of lending collateral on the funds' balance sheets over the sample period from 1996 to 2011. In Panel A, the volume is computed by aggregating over all government bond funds while the volume is the sum of the lending collateral of all corporate bond funds in Panel B. Our sample consists of 8,569 observations by 887 government bond funds and 7,215 observations by 834 corporate bond funds.

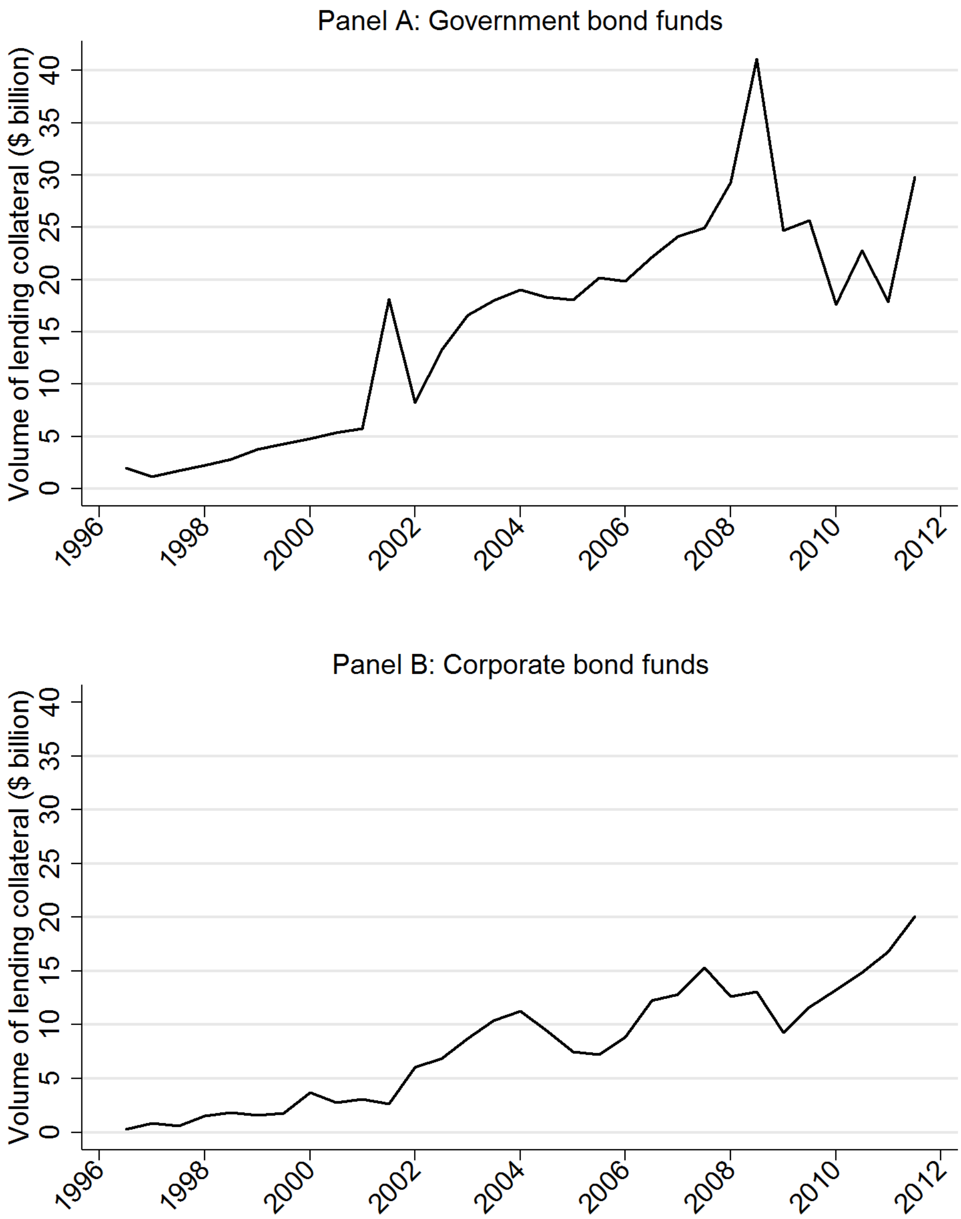
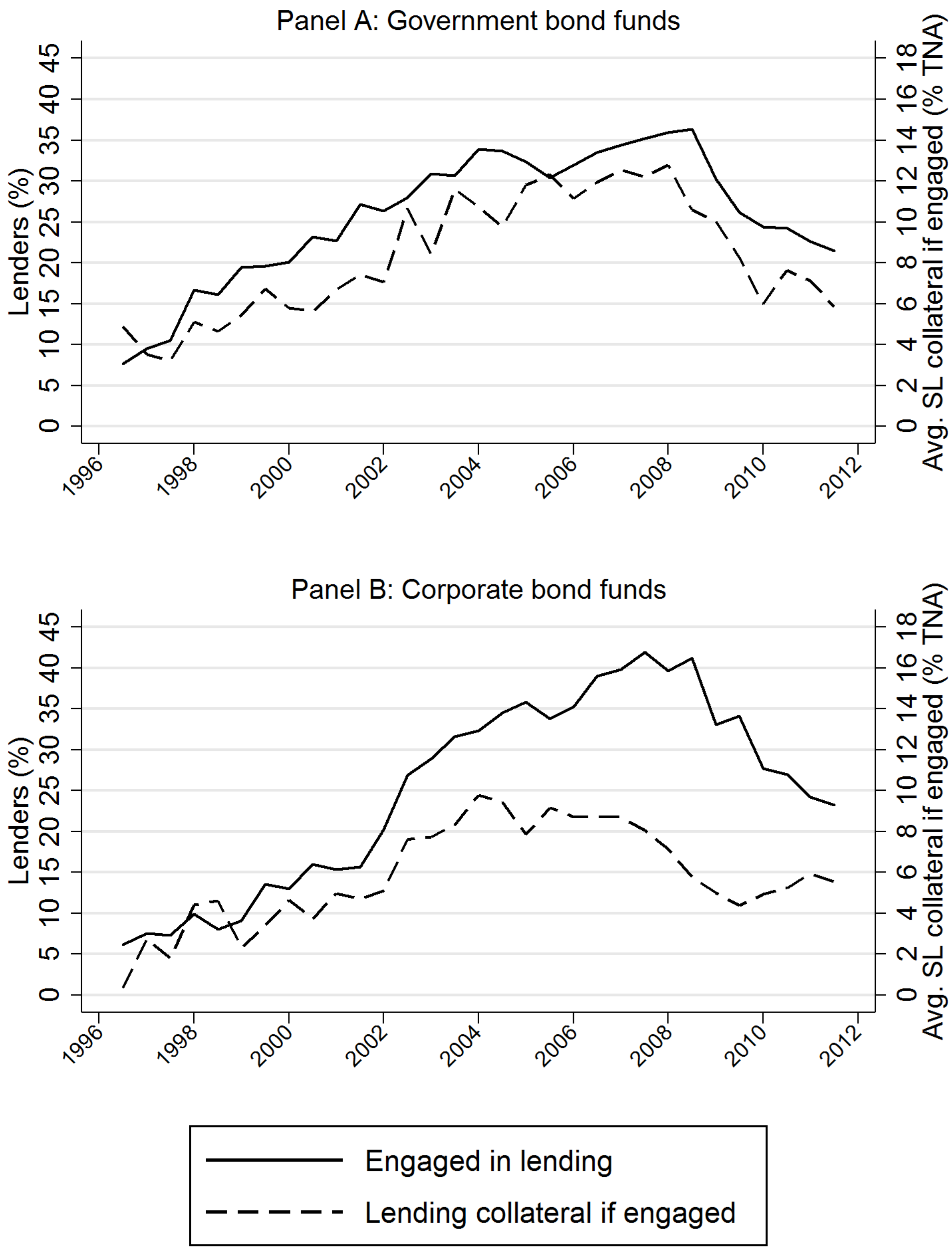


Figure 4: Securities lending activity

The solid line of this figure shows the fraction of funds engaged in securities lending over the sample period from 1996 to 2011. The dashed line represents the value of the average lending collateral as a percentage of TNA for all funds that have securities on loan at the respective period. The graphs displayed in Panel A are based on 8,569 observations by 887 government bond funds, while Panel B is based on 7,215 observations by 834 corporate bond funds.



A.2 Tables

Table 1: Securities lending collateral and other liabilities

Panel A of this table reports the average volume for seven distinct liability categories using data from 6,433 observations by 760 distinct funds that were engaged in securities lending over the past six months. In Panel B the category 'other liabilities' is decomposed for a random sample of 100 fund observations for which the lending collateral exceeded 10% of TNA. The decomposition is based on individual liability positions that are assigned to seven distinct liability categories. The percentages displayed in Panel A (Panel B) are computed by dividing the average volume of each liability category by the average amount of total liabilities (other liabilities).

	Ø Volume (mio USD)	**% Total**
Panel A: Breakup of liabilities using NSAR information		
Payables	87.36	51.60
Owed to affiliated persons	0.69	0.41
Senior long-term debt	0.17	0.10
Reverse repos	1.09	0.64
Short sales	2.84	1.68
Written options	0.33	0.20
Other liabilities (including SL collateral)	76.80	45.37
Panel B: Breakup of other liabilities using a random sample of 100 lenders		
Lending collateral	129.41	79.59
Payables	15.06	9.26
Dividends, fees and other expenses	0.63	0.39
Borrowings	9.64	5.93
Written options	6.33	3.89
Redeemed shares	1.39	0.86
Not-assignable liabilities	0.12	0.07

Table 2: Descriptive statistics: Securities lenders vs non-lenders

This table reports descriptive statistics for 887 government and 834 corporate funds during the sample period from 1996 to 2011. Fund characteristics for lenders and non-lenders are reported separately. Lenders are funds that were engaged in securities lending over the past six months. All variables are defined in Table A.I. Dummy variables are indicated by the suffix (Y/N).

Panel A: Government bond funds

	Lenders				**Non-lenders**			
	Mean	p50	Sd	#	Mean	p50	Sd	#
TNA (million USD)	886.47	362.87	1,514.56	2,672	746.98	188.13	1,672.21	6,403
Lending collateral (% TNA)	9.78	5.90	10.91	2,672	0.00	0.00	0.00	6,403
Fund age (years)	14.86	13.83	9.18	2,672	12.75	12.15	7.81	6,403
Retail (Y/N)	0.64	1.00	0.48	2,672	0.62	1.00	0.49	6,403
Family (Y/N)	0.80	1.00	0.40	2,672	0.76	1.00	0.43	6,403
Expenses (%)	0.76	0.73	0.31	2,672	0.77	0.73	0.35	6,403
Turnover (%)	209.08	142.50	223.09	2,672	187.73	104.00	255.03	6,403
Investments in ST securities (%)	11.07	7.53	12.56	2,672	10.18	4.86	15.97	6,403
6m netflows (%)	2.94	-2.71	36.81	2,672	7.46	-1.21	42.71	6,403
Standard deviation (%)	0.25	0.22	0.15	2,672	0.25	0.21	0.21	6,403
Beta	0.83	0.88	0.38	2,672	0.75	0.77	0.43	6,403
Idiosyncratic risk (%)	0.11	0.09	0.09	2,672	0.13	0.10	0.10	6,403
4f alpha$_{t-3;t+3}$ (%)	-1.33	-1.20	2.85	2,672	-0.98	-0.95	3.08	6,403
Almazan index	0.22	0.22	0.18	2,672	0.31	0.22	0.24	6,403
Depository (Y/N)	0.21	0.00	0.40	2,672	0.14	0.00	0.35	6,403
Risky agent (Y/N)	0.58	1.00	0.49	2,672	0.57	1.00	0.50	6,403

Continued on next page

Table 2: continued from previous page

Panel B: Corporate bond funds

	Lenders				Non-lenders			
TNA (million USD)	1,075.24	388.91	1,861.92	2,326	798.08	217.82	1,655.36	5,340
Lending collateral (% TNA)	6.91	4.26	7.33	2,326	0.00	0.00	0.00	5,340
Fund age (years)	14.26	12.12	9.96	2,326	12.00	9.75	9.47	5,340
Retail (Y/N)	0.63	1.00	0.48	2,326	0.61	1.00	0.49	5,340
Family (Y/N)	0.84	1.00	0.36	2,326	0.81	1.00	0.39	5,340
Expenses (%)	0.92	0.90	0.37	2,326	0.95	0.90	0.38	5,340
Turnover (%)	117.13	80.00	108.35	2,326	122.13	77.00	143.25	5,340
Investments in ST securities (%)	8.12	5.33	8.67	2,326	6.10	3.77	8.36	5,340
6m netflows (%)	3.91	-2.21	33.80	2,326	8.32	-0.42	43.96	5,340
Standard deviation (%)	0.28	0.23	0.19	2,326	0.27	0.24	0.16	5,340
Beta	0.58	0.49	0.45	2,326	0.54	0.45	0.44	5,340
Idiosyncratic risk (%)	0.19	0.15	0.14	2,326	0.19	0.16	0.14	5,340
4f alpha$_{t-3;t+3}$ (%)	-0.46	-0.63	4.09	2,326	-0.71	-0.69	4.21	5,340
Almazan index	0.18	0.11	0.14	2,326	0.23	0.22	0.19	5,340
Depository (Y/N)	0.13	0.00	0.34	2,326	0.09	0.00	0.28	5,340
Risky agent (Y/N)	0.65	1.00	0.48	2,326	0.62	1.00	0.48	5,340

Table 3: Securities lending and fund characteristics

This table reports marginal effects of multinominal logit regressions to relate fund characteristics to the lending activity of funds. The dependent variable in regression (1) and (3) is a dummy variable that equals one if the fund was engaged in securities lending over the past six months. The dependent variable in regression (2) and (4) is a dummy variable that equals one if a fund's lending collateral exceeds 5% of TNA in the respective period. All variables are defined in Appendix A.I. Marginal effects for each covariate are constructed as the difference in predicted probabilities for a particular outcome computed at their mean values holding all other covariates constant. The regressions are based on 887 government bond funds and 834 corporate bond funds during the sample period from 1996 to 2011. T-Values are reported in parentheses. Standard errors are heteroskedasticity robust and clustered at the fund level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	Government bond funds		**Corporate bond funds**	
	Lender	**Collateral > 5%**	**Lender**	**Collateral > 5%**
	(1)	(2)	(3)	(4)
Log(TNA)	0.188***	0.142***	0.163***	0.048**
	(11.41)	(6.96)	(9.16)	(2.05)
Family (Y/N)	0.127**	0.010	0.029	-0.122
	(2.20)	(0.14)	(0.41)	(-1.32)
Fund Age (years)	0.019***	0.016***	0.010***	0.003
	(5.99)	(4.24)	(3.66)	(0.79)
6m netflows (%)	-0.178**	-0.138	-0.255***	-0.481***
	(-2.41)	(-1.51)	(-3.27)	(-3.93)
Turnover (%)	0.001***	0.001***	-0.000*	-0.000
	(5.11)	(4.19)	(-1.74)	(-1.33)
Expenses (%)	-0.130	-0.211**	-0.187**	0.126
	(-1.64)	(-2.07)	(-2.45)	(1.26)
Retail (Y/N)	0.120**	-0.089	0.254***	-0.112
	(2.35)	(-1.40)	(4.60)	(-1.56)
Investment in ST securities (%)	0.003**	0.013***	0.026***	0.050***
	(2.04)	(7.65)	(9.11)	(14.75)
4f alpha$_{t\text{-}9;t\text{-}3}$	-3.283***	-2.497**	1.666**	-0.795
	(-3.89)	(-2.40)	(2.42)	(-0.91)
N	9,702	9,702	8,231	8,231
Adjusted (pseudo) R^2	0.0357	0.0450	0.0544	0.0765
Time fixed effects	Yes	Yes	Yes	Yes
Marginal effects	Yes	Yes	Yes	Yes

Table 4: Securities lending, fund risk and central depositories

This table reports OLS regressions relating fund risk to the lending activity of funds and the type of the lending agent. The dependent variable in regression (1) and (4) is the standard deviation of fund returns. The dependent variable in regression (2) and (4) is the regression coefficient obtained by regressing the U.S. aggregate bond index return on fund returns. The dependent variable in regression (3) and (6) is the variance of the residuals obtained by regressing the U.S. aggregate bond index return on fund returns. All dependent variables are computed over the six months around the reporting date at which the lending collateral is disclosed. Depository (Y/N) is a dummy variable that equals one if the lending agent of the fund is a central depository. All other variables are defined in Appendix A.I. The regressions are based on all bond funds that are engaged in securities lending at least once during the sample period from 1996 to 2011. T-Values are reported in parentheses. Standard errors are heteroskedasticity robust and clustered at the fund level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	Government bond funds			Corporate bond funds		
	SD	Beta	Idio	SD	Beta	Idio
	(1)	(2)	(3)	(4)	(5)	(6)
Collateral (%) * Depository (Y/N)	-0.0600**	-0.0009	-0.0005***	-0.0297	-0.0023*	-0.0006
	(-2.20)	(-0.89)	(-2.65)	(-0.39)	(-1.68)	(-0.94)
Depository (Y/N)	0.0117*	0.0001	0.0001	0.0191**	0.0002	0.0001
	(1.91)	(0.50)	(1.45)	(2.09)	(0.97)	(1.28)
Collateral (%)	0.0430**	0.0005	0.0004**	0.0002	0.0004	0.0001
	(2.25)	(1.07)	(2.24)	(0.01)	(0.42)	(0.26)
Ln(TNA)	0.0021	0.0000	0.0000	-0.0133***	-0.0002*	-0.0001***
	(0.65)	(0.34)	(0.60)	(-3.45)	(-1.84)	(-3.44)
Expenses	0.2586	0.0599*	-0.0028	-0.9654	0.0182	-0.0042
	(0.24)	(1.88)	(-0.31)	(-0.58)	(0.45)	(-0.29)
Turnover	0.0018**	0.0000*	0.0000	-0.0004	-0.0000	0.0000
	(2.09)	(1.87)	(1.57)	(-0.14)	(-0.13)	(0.03)
6m netflows	-0.0072***	-0.0001	-0.0001**	-0.0033	0.0000	-0.0000
	(-3.09)	(-1.50)	(-2.41)	(-0.84)	(0.47)	(-1.27)
4f $\text{alpha}_{t-9;t-3}$	-0.2560**	-0.0079***	-0.0025***	0.0489	-0.0030*	0.0008
	(-2.51)	(-3.40)	(-3.29)	(0.72)	(-1.94)	(1.31)
4f $\text{alpha}_{t-3;t+3}$	-0.3313***	-0.0010	-0.0039***	-0.3737***	0.0016	-0.0028***
	(-3.69)	(-0.50)	(-4.13)	(-4.97)	(0.99)	(-4.19)
N	5,123	5,123	5,123	4,636	4,636	4,636
Adjusted R^2	0.858	0.878	0.778	0.759	0.829	0.783
Fund fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
F-value($\beta_{Depository*C} + \beta_C = 0$)	0.745	0.160	1.672	0.199	3.218	0.829
p-value($\beta_{Depository*C} + \beta_C = 0$)	0.389	0.690	0.197	0.656	0.0736	0.363

Table 5: Securities lending, fund risk and risky agents

This table reports OLS regressions relating fund risk to the lending activity of funds and the type of the lending agent. The dependent variable in regression (1) and (4) is the standard deviation of fund returns. The dependent variable in regression (2) and (4) is the regression coefficient obtained by regressing the U.S. aggregate bond index return on fund returns. The dependent variable in regression (3) and (6) is the variance of the residuals obtained by regressing the U.S. aggregate bond index return on fund returns. All dependent variables are computed over the six months around the reporting date at which the lending collateral is disclosed. Risky agent (Y/N) is a dummy variable that equals one if the financial press reported about lending losses generated by the fund's lending agent at some point during the sample period. All other variables are defined in Appendix A.I. The regressions are based on all bond funds that are engaged in securities lending at least once during the sample period from 1996 to 2011. T-Values are reported in parentheses. Standard errors are heteroskedasticity robust and clustered at the fund level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	Government bond funds			Corporate bond funds		
	SD	Beta	Idio	SD	Beta	Idio
	(1)	(2)	(3)	(4)	(5)	(6)
Collateral (%) * Risky agent (Y/N)	0.0633**	0.0014	0.0514**	0.0847	0.0016	0.1040*
	(2.20)	(1.60)	(2.36)	(1.25)	(1.21)	(1.69)
Risky agent (Y/N)	0.0030	-0.0000	0.0088*	-0.0025	0.0000	-0.0015
	(0.56)	(-0.22)	(1.88)	(-0.37)	(0.31)	(-0.25)
Collateral (%)	-0.0083	-0.0005	-0.0053	-0.0641	-0.0012	-0.0736
	(-0.40)	(-0.68)	(-0.37)	(-1.27)	(-1.24)	(-1.55)
Ln(TNA)	0.0022	0.0000	0.0012	-0.0132***	-0.0002*	-0.0113***
	(0.64)	(0.32)	(0.48)	(-3.42)	(-1.81)	(-3.41)
Expenses	0.2927	0.0591*	-0.2501	-0.8075	0.0213	-0.3140
	(0.27)	(1.84)	(-0.27)	(-0.48)	(0.53)	(-0.22)
Turnover	0.0016*	0.0000*	0.0010	-0.0002	-0.0000	0.0002
	(1.96)	(1.88)	(1.42)	(-0.08)	(-0.13)	(0.09)
6m netflows	-0.0071***	-0.0001	-0.0051**	-0.0037	0.0000	-0.0046
	(-2.99)	(-1.43)	(-2.37)	(-0.91)	(0.41)	(-1.31)
4f alpha$_{t-9;t-3}$	-0.2585**	-0.0079***	-0.2469***	0.0468	-0.0030*	0.0768
	(-2.53)	(-3.39)	(-3.31)	(0.69)	(-1.94)	(1.27)
4f alpha$_{t-3;t+3}$	-0.3314***	-0.0010	-0.3879***	-0.3742***	0.0016	-0.2810***
	(-3.69)	(-0.49)	(-4.13)	(-4.98)	(1.02)	(-4.20)
N	5,112	5,112	5,112	4,636	4,636	4,636
Adjusted R^2	0.858	0.879	0.779	0.759	0.829	0.783
Fund fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
F-value($\beta_{RiskyAgent*C} + \beta_C = 0$)	7.057	2.977	6.175	0.188	0.196	0.503
p-value($\beta_{Riskyagent*C} + \beta_C = 0$)	0.00820	0.0852	0.0133	0.665	0.659	0.479

Table 6: Fixing the fund-agent relationship

This table reports OLS regressions relating fund risk to the lending activity of funds and the type of the lending agent. To address endogeneity concerns, the agent-fund relationship is fixed at each fund's first observation in the sample. Funds are excluded from the analysis if the fund was already engaged in securities lending at the fund's first or second observation. The dependent variable in regression (1) and (4) is the standard deviation of fund returns. The dependent variable in regression (2) and (4) is the regression coefficient obtained by regressing the U.S. aggregate bond index return on fund returns. The dependent variable in regression (3) and (6) is the variance of the residuals obtained by regressing the U.S. aggregate bond index return on fund returns. All dependent variables are computed over the six months around the reporting date at which the lending collateral is disclosed. Depository (Y/N) is a dummy variable that equals one if the lending agent of the fund is a central depository. Risky agent (Y/N) is a dummy variable that equals one if the financial press reported about lending losses generated by the fund's lending agent at some point during the sample period. All other variables are defined in Appendix A.I. The regressions are based on all bond funds that are engaged in securities lending at least once during the sample period from 1996 to 2011. T-Values are reported in parentheses. Standard errors are heteroskedasticity robust and clustered at the fund level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	Government bond funds					
	Central depositories			Risky agents		
	SD	Beta	Idio	SD	Beta	Idio
	(1)	(2)	(3)	(4)	(5)	(6)
Collateral (%) * $\text{Depository}^{\text{Fixed}}$ (Y/N)	-0.08**	-0.00*	-0.04			
	(-2.48)	(-1.69)	(-1.59)			
Collateral (%) * Risky $\text{agent}^{\text{Fixed}}$ (Y/N)				0.05*	0.00	0.05*
				(1.69)	(1.10)	(1.89)
Collateral (%)	0.04*	0.00	0.03	-0.01	-0.00	-0.01
	(1.79)	(1.52)	(1.34)	(-0.68)	(-0.36)	(-0.77)
Ln(TNA)	0.00	0.00	-0.00	0.00	0.00	-0.00
	(0.96)	(0.55)	(-0.43)	(0.76)	(0.49)	(-0.66)
Expenses	0.79	0.10***	0.31	0.51	0.09***	-0.24
	(0.45)	(2.65)	(0.25)	(0.31)	(2.69)	(-0.21)
Turnover	0.00	0.00	-0.00	0.00	0.00	-0.00
	(0.47)	(0.91)	(-0.48)	(0.57)	(1.00)	(-0.41)
6m netflows	-0.00*	-0.00***	0.00	-0.00*	-0.00***	0.00
	(-1.74)	(-4.69)	(0.24)	(-1.91)	(-4.78)	(0.53)
4f $\text{alpha}_{\text{t-9;t-3}}$	-0.27**	-0.01***	-0.27***	-0.29**	-0.00**	-0.25***
	(-2.20)	(-2.80)	(-3.37)	(-2.53)	(-2.03)	(-3.31)
4f $\text{alpha}_{\text{t-3;t+3}}$	-0.53***	-0.00	-0.54***	-0.57***	-0.00	-0.49***
	(-2.92)	(-0.61)	(-4.39)	(-3.20)	(-0.63)	(-4.31)
N	3,184	3,184	3,184	3,499	3,499	3,499
Adjusted R^2	0.788	0.853	0.719	0.805	0.854	0.737
Fund fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: Government vs. corporate bond funds

This table reports OLS regressions relating fund risk to the lending activity of funds and the type of the fund. The dependent variable in regression (1), (4) and (7) is the standard deviation of fund returns. The dependent variable in regression (2), (5) and (8) is the regression coefficient obtained by regressing the U.S. aggregate bond index return on fund returns. The dependent variable in regression (3), (6) and (9) is the variance of the residuals obtained by regressing the U.S. aggregate bond index return on fund returns. All dependent variables are computed over the six months around the reporting date at which the lending collateral is disclosed. All other variables are defined in Appendix A.I. The regressions are based on all bond funds that are engaged in securities lending at least once during the sample period from 1996 to 2011. T-Values are reported in parentheses. Standard errors are heteroskedasticity robust and clustered at the fund level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	All sample funds								
	SD	**Beta**	**Idio**	**SD**	**Beta**	**Idio**	**SD**	**Beta**	**Idio**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Government * SL collateral (%)	0.0475*	0.0002	0.0004*	0.1132**	0.0013	0.0008*	0.1545***	0.0012	0.0013***
	(1.80)	(0.25)	(1.82)	(2.37)	(1.37)	(1.91)	(2.97)	(1.02)	(2.71)
SL collateral (%)	-0.0130	0.0001	-0.0002	-0.0448	-0.0005	-0.0003	-0.1048*	-0.0006	-0.0011**
	(-0.59)	(0.20)	(-0.80)	(-0.96)	(-0.52)	(-0.76)	(-1.95)	(-0.59)	(-2.27)
Government (Y/N)	-10431.19	54.72	-109.06	-85.13	1.32	-0.66	2482.43	-158.11	25.20
	(-0.00)	(0.00)	(-0.00)	(-0.00)	(0.00)	(-0.00)	(0.00)	(-0.00)	(0.00)
Ln(TNA)	-0.01***	-0.00***	-0.00***	-0.01***	-0.00***	-0.00***	-0.00	-0.00**	-0.00*
	(-4.61)	(-4.66)	(-5.30)	(-2.71)	(-2.72)	(-2.74)	(-1.12)	(-2.07)	(-1.66)
Expenses	-1.58**	0.05***	-0.01**	-1.39	0.07*	-0.01	0.36	0.10**	-0.01
	(-2.29)	(3.10)	(-2.46)	(-1.10)	(1.92)	(-0.74)	(0.17)	(2.23)	(-0.37)
Turnover	0.00	0.00**	0.00	0.00	0.00	0.00	0.00**	0.00	0.00
	(0.89)	(2.12)	(0.53)	(0.82)	(0.55)	(0.34)	(2.51)	(0.61)	(1.60)
6m netflows	-0.01**	0.00	-0.00***	-0.01*	0.00	-0.00***	-0.01***	0.00	-0.00***
	(-2.55)	(0.09)	(-3.00)	(-1.95)	(0.93)	(-3.34)	(-2.74)	(1.26)	(-2.82)
Past 4f alpha	-0.15***	-0.01***	-0.00***	-0.16***	-0.01***	-0.00**	-0.00	-0.00***	0.00
	(-4.41)	(-6.98)	(-3.63)	(-2.71)	(-4.19)	(-2.12)	(-0.00)	(-2.89)	(0.47)
N	10,120	10,120	10,120	9,238	9,238	9,238	6,507	6,507	6,507
Adjusted R^2	0.776	0.836	0.759	0.787	0.846	0.777	0.791	0.875	0.772
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Agent x time fixed effects	No	No	No	Yes	Yes	Yes	No	No	No
Family x time fixed effects	No	No	No	No	No	No	Yes	Yes	Yes

Table 8: Securities lending and fund performance

This table reports OLS regressions relating fund performance to the lending activity of funds and the type of the lending agent. The dependent variable is a fund's four factor alpha over the six month around the date at which the lending collateral is disclosed. Depository (Y/N) is a dummy variable that equals one if the lending agent of the fund is a central depository. Risky agent (Y/N) is a dummy variable that equals one if the financial press reported about lending losses generated by the fund's lending agent at some point during the sample period. All other variables are defined in Appendix A.I. The regressions are based on all bond funds that are engaged in securities lending at least once during the sample period from 1996 to 2011. T-Values are reported in parentheses. Standard errors are heteroskedasticity robust and clustered at the fund level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	4f alpha$_{t-3;t+3}$			
	Government bond funds		Corporate bond funds	
	(1)	(2)	(3)	(4)
Collateral * Depository	-0.00		-0.01	
	(-0.07)		(-0.78)	
Collateral * Risky agent		-0.00		0.02
		(-0.59)		(1.50)
Collateral * Almazan index	0.04***	0.04***	-0.04	-0.05
	(2.70)	(3.09)	(-0.91)	(-1.12)
Collateral (%)	-0.01	-0.01	0.02	0.00
	(-1.37)	(-1.31)	(1.38)	(0.26)
Almazan index	0.00	0.00	-0.00	0.00
	(1.34)	(0.81)	(-0.52)	(0.79)
Depository (Y/N)	-0.00		0.00	
	(-0.15)		(0.93)	
Risky agent (Y/N)		0.00		-0.00*
		(0.19)		(-1.81)
Ln(TNA)	-0.00***	-0.00***	-0.01***	-0.01***
	(-4.28)	(-4.68)	(-6.03)	(-6.93)
Expenses	-0.57**	-0.56**	0.51	0.65
	(-2.15)	(-2.15)	(1.07)	(1.47)
Turnover	-0.00	-0.00	0.00	0.00**
	(-1.39)	(-1.27)	(1.58)	(1.98)
6m netflows	-0.00	-0.00	0.00	0.00
	(-0.11)	(-0.17)	(0.55)	(0.26)
N	4,785	5,064	4,128	4,374
Adjusted R^2	0.505	0.509	0.439	0.438
Fund fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
F-value($\beta_{Agenttype*C} + \beta_C = 0$)	2.032	3.281	0.328	2.931
p-value($\beta_{Agenttype*C} + \beta_C = 0$)	0.155	0.071	0.567	0.088

A.3 Variable definitions

Table A.I: Variable Definitions

Variable Name	Definition	Source
Lending variables:		
Lender	Dummy variable that equals one if a fund was engaged in securities lending over the past six months.	N-SAR
Lending (SL) collateral	80% of other liabilities if a fund lends out securities and zero otherwise.	N-SAR
Lending agent definitions:		
Central depository	Dummy variable that equals one if a fund declares that its custodian falls under Rule 17f-2.	N-SAR
Risky agent	Dummy variable that equals one if a fund's custodian was mentioned in the financial press in connection with securities lending losses.	Press
Fund characteristics:		
6m netflows	The sum of monthly netflows over the past six months divided by TNA of the previous period, where monthly netflows are computed by the following formula: $\text{TNA}_{i,t} - \text{TNA}_{i,t-1} \cdot (1 + \text{Fund return}_{i,t})$	CRSP
Turnover	Minimum of total purchases and total sales over the monthly average value of the portfolio.	CRSP
Expenses	A fund's operating expenses including 122b-1 fees over TNA.	CRSP
Retail	Dummy variable that equals one if the majority of share classes is catered to retail investors.	CRSP
Investment in ST securities	Percentage of assets invested in securities with a maturity of less than 1 year.	NSAR

Continued on next page

Table A.I: continued from previous page

Variable Name	Definition	Source
Leverage index	Average value of three dummy variables that equal one if a fund is not permitted to (i) borrow money, (ii) purchase on margin and (iii) sell securities short.	NSAR
Derivatives index	Average value of two dummy variables that equal one if a fund is not permitted to (i) write or invest in debt options and (ii) write or invest in interest rate futures.	NSAR
Illiquid assets index	Dummy variable that equals one if a fund is not permitted to invest in restricted securities.	NSAR
Almazan index	Average value of the leverage, derivatives, and illiquid assets index.	NSAR
Risk and performance measures:		
SD	Standard deviation of fund returns over the six months around the reporting date.	CRSP
Beta	Coefficient obtained by regressing the U.S. aggregate bond index return on fund returns over the six months around the reporting date.	CRSP
Idio	Variance of residuals obtained by regressing the return of the U.S. aggregate bond index on fund returns over the six months around the reporting date.	CRSP
4f alpha	Fund return$_{i,t}$ $-\sum_{k=1}^{4}$ factor return$_{k,t}$ $*\ \beta_{i,k,t}$, where $\beta_{i,k,t}$ is computed for fund i and factor k over the past 250 trading days. The factors are: (i) the return of the US aggregated bond index, (ii) the return of the stock market, (iii) a default, and (iv) a mortgage factor.	Datastream, CRSP, FF

End-of-Period Trading by Mutual Funds

Hermann Elendner   Laurenz Klipper

Abstract:

We provide an easy way to measure the trading activity by mutual funds in the last three days of their reporting periods. Heavy end-of-period (EoP) traders report more winner and fewer loser stocks, yet perform no better. Consistent with window dressing, their rank and return gaps loom higher. Stocks with a high positive EoP trade imbalance experience significant price increases of about 20 bps over those three days. Inconsistent with information trading, prices revert within a week. In line with price pressure from institutional investors, liquid stocks appreciate less strongly and revert more quickly. Period-ends differ, however, across calendar months: stocks with a high EoP imbalance appreciate at the end of all months, but reversals only follow if funds report in June or December. Finally, we show window dressing, portfolio pumping, or fund flows alone are unlikely to explain our results.

Keywords: Mutual funds, end-of-period trading, price pressure, reversal, window dressing, portfolio pumping

JEL-Classification: G23, G14, G12

1 Introduction

Since mutual fund holdings are only disclosed quarterly, the academic literature has struggled to overcome the challenge of examining the trading activity of funds over shorter horizons. We show that there exists easily accessible information that allows for an accurate and reliable measurement of mutual fund trading over the last three days of each fund's reporting period. While this data is limited to end of reporting periods, it is available for the entire mutual fund industry and offers a new opportunity to analyze the trading behavior within this industry. The objective of this study is to provide a detailed examination of the extent of, motivation for, and economic impact of end-of-period trades by mutual funds.

End-of-period trades by mutual funds are observable since equity transactions typically require three days to be settled.[1] For accounting purposes, unsettled trades show up as account payables and receivables on the funds' balance sheets. Consequently, the balance sheet at a reporting date reveals the total purchase and sale volume that each fund has effected during the three-day settlement period preceding this date.

We collect these volumes for a broad sample of 2,508 US equity funds from 1998 to 2011 and proceed along three lines of inquiry.[2] First, we compare the trading volume at period-ends with the average volume in-between disclosures. While this difference is small in aggregate, we find considerably cross-sectional and time-series variation on the individual fund level. While some funds trade particularly actively during the last three days of their reporting periods, others persistently avoid any trading during this period.

[1] Non-equity trades have shorter settlement periods, ranging from 1 to 3 days.

[2] Balance sheet data can be obtained by collecting SEC N-SAR forms available from EDGAR.

The second part of our analysis relates the trading activity of funds at the end of their reporting period to return and fund characteristics as well as to stock characteristics in an effort to understand the motives behind these trades. In order to organize and limit the scope of our empirical analysis, we consider the following four reasons for end-of-period trading: (i) information-based trading, (ii) window dressing, (iii) portfolio pumping, and (iv) flow-induced trading. Information-based trading refers to trades that are enacted because fund managers possess superior information about stock fundamentals (see Chen, Jegadeesh, and Wermers 2000; Wermers 2000 for evidence about stock-picking abilities by mutual fund managers). Window dressing denotes the practice of adjusting the holdings prior to disclosure date in order to provide a misleading picture in mandatory reports (Lakonishok, Shleifer, Thaler, and Vishny, 1991; Musto, 1999; Agarwal, Gay, and Ling, 2014). Portfolio pumping is the alleged activity of manipulating closing prices of fund holding upwards through large last-minute orders that exert price pressure (Carhart, Kaniel, Musto, and Reed, 2002; Hu, McLean, Pontiff, and Wang, 2014). Lastly, flow-induced trading may arise because of sudden investor inflows or outflows forcing a fund to sell or buy assets (Coval and Stafford, 2007).

We do not find evidence that end-of-period trading is related to possessing proprietary information about stock fundamentals. Funds that exhibit high end-of-period trades do not achieve superior performance subsequent to those trades. If anything, they perform worse when compared to funds with low end-of-period trading activity, consistent with uninformed trades incurring transaction costs.

In support for window dressing, funds with large end-of-period trade disclose more winner and fewer loser stocks. Heavy end-of-period traders also tend to exhibit higher rank gaps and backward holding return gaps, thus scoring higher on the two standard measures for window dressing. In line with these findings, stocks that receive large purchase orders performed well over the previous period.

Portfolio pumping does not appear related to end-of-period trading. Large end-of-period trades are not associated with high last-day fund returns, a finding that would be expected if funds inflate their holding positions.

We find a strong relation between fund flows and trading at the last days of the reporting period. Funds' netflows tend to be high for funds with a large purchase volume, while they are low for heavy end-of-period sellers. This suggests that some buys and sales at the end of a fund's reporting period are driven by the necessity to react on provision or withdrawal of capital.

In our third line of inquiry, we examine the impact of end-of-period trades on stock prices. Since the balance-sheet information about end-of-period trading does not include a breakdown into individual securities, we need to impute which stocks are traded at the end of a period from holding changes. We then aggregate the imputed end-of-period stock buys and sales over all funds for each individual stock to obtain a proxy for the aggregate trade imbalance from the mutual fund industry.

When we sort stocks along this trade imbalance, we find that those with strong demand overhang (i.e. strong positive net trade imbalances) experience significant price increases of about 20 bps during the last three days of the period. This price effect is obtained after controlling for stock and time fixed effects and after adjusting stock returns for their sensitivity to the (i) market, (ii) size, (iii) value-to-book, and (iv) momentum factors (Carhart, 1997). Interestingly, we do not find a similar price effect on the sell side.[3]

[3] One potential explanation for not observing price effects for stocks with a large supply overhang is outside liquidity. If outside investors provide sufficient liquidity to satisfy all sell orders, market prices will not change. We, however, have no clear theoretical explanation why liquidity problems arise on the buy, but not on the sell side.

While the price effects on the buy side persist in most months of the calendar year, the price appreciation observed in December and June is followed by strong reversals over the following month.[4] This suggests that trades at the end of the half-year and at the end of the year are not driven by fundamental information. Rather, the findings are consistent with temporary price pressure induced by mutual fund trading as described by Scholes (1972). In line with this theory, price appreciations are more pronounced and take longer to revert for less liquid stocks when compared to liquid stocks.

Finally, we explore whether the temporary price effect observed in December and June can be linked to window dressing, portfolio pumping, or fund flows. For that purpose, we split our fund sample into two halves along the median of either our window-dressing indicators, last day fund returns, or fund flows. For each of those splits, we find the link of end-of-period net trades and stock prices to be present both in the above and below-median sub-sample. This suggest that price increases and reversals are not driven by one of these trading motives alone.

To the best of our knowledge, our paper is the first comprehensive examination of the trading activity of mutual funds at the end of their reporting period. The work closest to our paper is the study by Hu et al. (2014), who use a proprietary sample of daily trades by 150 unknown equity funds to examine whether institutional investors are engaged in window dressing or portfolio pumping. By studying trades that are based on almost the entire mutual fund industry and by studying the economic impact of these trades, we offer a more complete perspective on end-of-period trading. Our analysis of the relation between end-of-period trading and stock prices is related to previous studies that document a link between mutual fund trading and stock price movements (Coval and Stafford, 2007; Lou, 2012). While these studies focus on forced

[4] Funds in December and June appear to be similar to funds in other months of the year. Hence, the result differences are unlikely driven by selection-effect explanations.

trading induced by fund flows, our results are not explainable by inflows or outflows, but rather appear to be largely driven by voluntary trades at the end of the period.

The remainder of the paper is structured as follows. Section 2 reviews the literature and offers a theoretical framework for the empirical analysis. Section 3 introduces our data set and our measures. Section 4 presents the results from our empirical analyses. Section 5 describes several robustness tests. Section 6 concludes.

2 Conceptual framework

In this section we offer a conceptual framework for the examination of the potential motives for, and the economic impact of end-of-period trading. Based on the prior literature, we review the theory on which our empirical tests and their interpretation are based.

2.1 Motives for end-of-period trading

Fundamentally, trades fall into two categories: those driven by information about the securities bought or sold, and those carried out for reasons unrelated to information. In the following, we develop testable hypotheses to differentiate between information-based and different non-information based trading motives. We test these hypotheses in Section 4.2.

2.1.1 Information-based trading activity

One explanation for high trading volumes at the end of reporting periods is private information. Many period-ends of funds coincide with enterprises finalizing quarterly reports, such that heightened information arrival is well conceivable. If this information arrival varies across funds, heterogeneous trading levels in the cross-section as well as in the time-series should naturally arise.

To identify those trades, we examine the performance of funds that show large EoP trades. If EoP trades are motivated by an informational advantage, funds should profit from EoP trades by generating higher returns over the following months.[5]

2.1.2 Non-information based trading activity

In contrast to information-based trades, trades unrelated to information should not translate into higher fund returns. In fact, uninformed trades could even be detrimental to fund performance due to transaction costs. Hence, we can differentiate between informed and uninformed trading by examining the fund performance subsequent to the reporting date.

We also want to differentiate between different motives for uninformed trading. The literature has modeled an array of incentives for fund managers to execute EoP trades, even without possessing superior information:

Window Dressing. One motive for such trading is window dressing. The purpose of window dressing is to mislead investors by disclosing disproportionally higher holdings in stocks that showed strong past performance, or disproportionally lower holdings of poorly performing stocks (Lakonishok et al., 1991).[6] The literature has developed two measures to capture window-dressing behavior: First, the backward holding return gap (BHRG), and, second, the rank gap.[7] Both measures are detailed in Appendix A.I and identify window dressers by calculating the discrepancy between a fund's true performance and the performance of a hypothetical portfolio based on the reported holdings of the fund. A fund is classified as a window dresser if the performance of its

[5] We analyze fund returns up to six months after the reporting date.

[6] Note that our measures are only capable of capturing window dressing if trades are executed in the last three days of the funds' reporting period. Earlier holding adjustments will remain undetected.

[7] The BHRG was introduced by Lakonishok et al. (1991), while the rank gap was first presented by Agarwal et al. (2014).

disclosed holdings exceeds its actual performance. If window dressing drives EoP trading, heavy EoP traders should, therefore, show large backward holding return and rank gaps. Moreover, the portfolio of funds with large EoP trades should consist of a larger (lower) proportion of winner (loser) stocks.[8] Finally, EoP purchases should predominantly target stocks with high past performance, while sales should target poorly performing stocks. Therefore, window-dressing behavior should lead to a relation between the amount of EoP trades and these window-dressing indicators.

Portfolio Pumping. A different strategy for funds to influence disclosures is to *deliberately* inflate stock prices by creating price pressure through aggressive trading immediately before the period-end. This practice, known as "painting the tape," "marking up," or "portfolio pumping," is driven by the managers' attempt to improve the reported current performance of the fund. Empirical evidence for such a behavior has been documented by Carhart et al. (2002) and Hu et al. (2014).[9] Because portfolio pumping is intended to improve fund performance, we expect portfolio pumpers to show high returns at the last day of the reporting period. Moreover, their trades should occur predominantly in stocks with low market liquidity, which should react more strongly to induced price pressure. While we test the first prediction by examining the funds' last-day returns, we test the second hypothesis by studying the liquidity of stocks with large EoP purchase orders.

Fund flows Apart from disclosure management, end-of-period trading could also be triggered by capital inflows and outflows. A sudden withdrawal of liquidity will require the fund to sell assets, while incoming capital typically results in purchase orders. We analyze whether there is evidence for flow-

[8] Winner stocks are defined as those in the highest performance quintile over the last quarter; loser stocks as those in the lowest.

[9] Since portfolio pumping necessarily occurs at the very last moment, the corresponding trading activity will be fully captured by our EoP measures.

induced trading at the end of reporting periods by studying whether higher EoP buy volumes are linked to higher net flows (and higher sell volumes to lower flows) during the reporting period.

Other reasons Finally, end-of-period trading might also be related to other motives, such as portfolio re-balancing, tax evasion, or the desire to reach certain turnover targets. Due to the important role information-based trading and disclosure-management practices play in the extant literature, we leave such other potential reasons outside the scope of this paper.

2.2 The economic impact of end-of-period trading

Since mutual funds are the largest and most active traders in equity markets, it is important to understand whether and how their trades impact these markets. We address this question by examining stock price reactions to end-of-period trades.

2.2.1 Stock price impact

A large body of literature shows that trading is linked to asset-price movements. The market maker literature offers a theory that can explain these price movements. In the models of this literature, market makers manage their inventories by adjusting their price quotes. When market makers receive large volumes of buy (sale) orders, their inventory level falls (increases). They react on these inventory changes by increasing or decreasing the asset price until their inventory is back to their target level (Kyle, 1985). Similarly, the price hypothesis by Scholes (1972) predicts temporary stock price changes in response to excess demand or supply. Consistent with these theories, numerous studies including Gallant, Rossi, and Tauchen (1992), Hiemstra and Jones (1994), and Lo and Wang (2000) find a significant relationship between order imbalances and stock prices. We hypothesize similar asset price reactions to trade imbalances occurring at the end of reporting periods.[10]

2.2.2 Persistent vs. temporary stock price impact

Persistent stock price impact. If asset prices react to end-of-period trading, the price change can persist or be temporary in nature. The most obvious reason for a persistent price change is an order imbalance that arises due to new information about the fundamentals of an asset. If the new information set suggests that the asset was undervalued (overvalued), excess buy orders increase (decrease) the asset price until the price reflects the new fundamental value (Kyle, 1985; Kelley and Tetlock, 2013).

Temporary stock price impact. In contrast, price movements can also be caused by order imbalances that are not driven by fundamental information. Market prices may react to these imbalances initially, but eventually revert back to their fundamental values (Andrade, Chang, and Seasholes, 2008; Grossman and Miller, 1988). In light of these arguments, we examine stock price reversals in Section 4.3 to differentiate between information-based and uninformed stock price movements.

2.2.3 Stock price impact and stock liquidity

If price fluctuations are caused by price pressure, the price impact should vary with the liquidity of the respective stock. Less liquid stocks subject to a demand or supply shock should experience stronger initial price changes and slower reversals (Pastor and Stambaugh, 2003). We test this hypothesis by separately analyzing price changes of low and high liquidity stocks.

[10] We implicitly assume that order imbalances found in the mutual fund industry are not easily filled by other agents outside this industry.

2.2.4 Stock price impact and the motives of end-of-period trading

Temporary trade imbalances can arise for different reasons. One area of research implicitly examines the role of mutual fund flows in causing these imbalances. Funds subject to inflows or outflows are forced to trade. When these flows are correlated across funds, multiple funds need to place similar buy or sell orders at the same time. This can create an aggregate demand or supply overhang in certain stocks. Consistent with this idea, several studies, including Coval and Stafford (2007) and Jotikasthira, Lundblad, and Ramadorai (2012), provide evidence that stocks subject to flow-induced trading show temporary price movements.

In contrast to trade imbalances that arise by flow-induced trading, mutual funds may also engage in portfolio pumping to deliberately inflate asset prices, as discussed in the previous section. Potential portfolio pumpers are identified by showing large returns during the last day of their reporting period. We test whether trades by these funds impact stock prices differently than trades by funds with low last-day returns.

Finally, order imbalances can be caused by herding. Shiller, Fischer, and Friedman (1984), De Long, Shleifer, Summers, and Waldmann (1990), and Shleifer and Summers (1990), for example, posit that stocks experience excess demand or supply because multiple investors at times follow certain fads or place greater importance on the same news. Mark Grinblatt (1995), Falkenstein (1996) and Guercio (1996) relate herding to certain trading strategies. Scharfstein and Stein (1990), Lakonishok et al. (1991), and Lakonishok, Shleifer, and Vishny (1994) argue that herding may arise due to agency problems, such as window dressing. We examine the latter argument by testing whether trades by potential window dressers exhibit different price reactions as compared to trades by funds unlikely to be window dressers.

3 Data

This section outlines the data set and explains the construction of the end-of-period trading measures. We construct trading measures on the fund and stock level. Since the trading measures on the stock level rely on a number of assumptions, we relate them to the actual stock trading volume for validation.

3.1 Data source and sample selection

Our mutual fund sample is based on N-SAR forms, which must be filed semi-annually by all US investment companies registered with the SEC. We extract balance-sheet information and fund characteristics from all N-SAR forms available in the SEC EDGAR database for the time between 1998 and 2011.[11] We drop entries for which the fund name, the filing date, the balance-sheet data, or the turnover data are not identifiable or implausible.[12] We exclude all funds that indicate to be an index fund. Moreover, we drop all money-market funds, which are identified by having turnover ratios of zero, a non-missing mark-to-market net asset value per share, as well as a non-missing average daily net asset value during the period. We also remove a fund observation from our sample if the fund changes its reporting month, which is an indication for a fund restructuring, a merger, or other special events within the fund family.

To obtain information about general fund characteristics, daily returns and monthly net asset values, we link our data to the Center for Research in Security Prices (CRSP) Mutual Fund database using fund tickers or – if not available – fund names. To verify our matching procedure, we require that total net assets of both data sources do not deviate by more than 5% and

[11] Prior to 1998, N-SAR forms are not consistently available and contain unreliable balance-sheet data.

[12] Entries are deemed implausible if balance-sheet or turnover data are negative or accounts payables (receivables) exceed total purchases (sales) of the period.

manually check our data for mismatches.[13] We use MFLINKS to link our database to the Thomson Reuters S12 Ownership Database, which provides quarterly fund holdings.

In order to restrict our sample to US open-end equity funds, we follow Kacperczyk, Sialm, and Zheng (2008) by relying on (i) the investment objective code (IOC) provided by Thomson Reuters, (ii) the Strategic Insight Objective and (iii) the Wiesenberger Fund Type Code provided by CRSP, as well as (iv) the asset composition obtained from N-SAR forms. We start by removing all international (IOC code 1), municipal-bond (IOC code 5) and balanced funds (IOC code 7), as well as all bond and preferred funds (IOC code 6) from the sample. We then eliminate all funds whose Strategic Insight Objective Codes differ from the following equity investment objectives: AGG, GMC, GRI, GRO, ING, and SCG. If the fund does not have a valid Strategic Objective Code, we instead rely on the Wiesenberger Fund Type Codes and require the fund to have one of the following codes: G, G-I, AGG, GCI, GRI, GRO, LTG, MCG, and SCG. Since some funds have neither a valid Strategic Objective nor a Wiesenberger Fund Type Code, we finally exclude all funds that have less than 80% of their assets invested in common stocks.

To address the incubation bias in the CRSP database identified by Elton, Gruber, and Blake (2001) and Evans (2010), we remove all observations of a fund that reports less than $5 million in assets under management in the previous month. This leaves us with a final data set of 21,928 half-year observations generated by 2,508 US equity funds during the sample period ranging from 1998 to 2011.

[13] We tolerate a difference of up to 5% in order to account for rounded values and missing share classes in the CRSP database.

3.2 End-of-period trading measures

We use our data set to construct two trading measures. The first measure captures the end-of-period trading volume at the fund level. The second measure is at the stock level and proxies how end-of-period trades are allocated to individual stocks.

3.2.1 Measuring end-of-period fund trading

One of the major contributions of this paper is to document that balance-sheets contain information about each fund's trading volume during the last three days of the reporting period. Mutual funds are obliged to report balance-sheet data twice a year to the SEC, including information about their accounts payables for instruments purchased and accounts receivables from instruments sold.[14] For mutual funds accounts payables and receivables arise from security transactions that are not yet settled.

The SEC requires transaction partners to settle equity trades within three trading days. Following this requirement, a settlement period of three days has been established as industry standard for equity transactions.[15] In the three-day settlement period a fund will report all unsettled trades in the form of payables (for securities purchased) and receivables (from securities sold) on its balance sheet; holdings, however, are updated immediately. Hence, the disclosed amounts of accounts payables and receivables at a reporting date disclose – with audited quality – a fund's total trading volume over the last three days of the respective reporting period. For convenience, we refer to the dollar amounts of accounts payables and receivables as end-of-period (EoP) fund buys and sales:

[14] Payables and receivables are reported in items 74.O and 74.J of the SEC N-SAR form.

[15] The required settlement period for non-equity trades is usually shorter. For example, certificates of deposit and commercial paper must be settled on the same day, US treasuries are settled within one day, and the settlement period of foreign-exchange transactions is two days.

$$EoP\ fund\ buys_{i,t} = Payables\ for\ instruments\ purchased_{i,t}$$
$$EoP\ fund\ sales_{i,t} = Receivables\ from\ instruments\ sold_{i,t} \tag{1}$$

3.2.2 Measuring stock trades at funds' period-ends

In order to identify potential effects of end-of-period trading on stock prices, we need a trading measure at the level of individual stocks. However, while the disclosed EoP trading activity of funds differentiates purchases from sales, each of those two volumes is an aggregate with no breakdown into the transactions at a security level. Therefore, we have to rely on quarterly changes in fund holdings to proxy for the amount of purchases and sales per stock. This is achieved by imputing for each stock j at month t the following buy measure:

$$EoP\ stock\ buys_{j,t} = \frac{\sum_{i \in Funds} EoP\ fund\ buys_{i,t} \cdot w_{ijt}^{buys}}{Mcap_{jt}},$$
$$\text{where} \qquad w_{ijt}^{buys} = \frac{Shares\ bought_{ijt} \cdot p_{jt}}{\sum_{k \in Stocks} Shares\ bought_{ikt} \cdot p_{kt}} \tag{2}$$

$Mcap_{jt}$ and p_{jt} are the market capitalization and the price of stock j at the end of month t, respectively. $Shares\ bought_{ijt}$ is the increase in shares of stock j by fund i from month $t-3$ to month t. Intuitively, the variable *EoP stock buys* captures to what extent a given stock j was purchased by our sample funds over the last three days of month t.[16] It is constructed by allotting each fund's end-of-period buys to stocks that the fund has bought over the last quarter, putting more weight on large holding increases and less weight on small holding increases of the fund. Stock end-of-period (EoP) buys_{jt} are the

[16] Note that funds report in different months of the year. Hence, we capture only trades of funds that report in a given month.

sum of all EoP fund buys that were assigned to stock j, scaled by the stock's market capitalization.

Following an analogous procedure, we construct *EoP stock sales*$_{j,t}$[17]:

$$\begin{aligned} EoP\ stock\ sales_{j,t} &= \frac{\sum_{i \in \text{Funds}} EoP\ fund\ sales_{i,t} \cdot \mathrm{w}^{\text{sales}}_{ijt}}{\text{Mcap}_{jt}}, \\ \text{where} \qquad \mathrm{w}^{\text{sales}}_{ijt} &= \frac{\text{Shares sold}_{ijt} \cdot p_{jt}}{\sum_{k \in Stocks} \text{Shares sold}_{ikt} * p_{kt}} \end{aligned} \tag{3}$$

We define the total trading volume of a stock as the sum of stock buys and stock sales. We take the difference of EoP stock buys and EoP stock sales to compute each stock's aggregate net trade imbalance:

$$EoP\ total\ trades_{j,t} = EoP\ stock\ buys_{j,t} + EoP\ stock\ sales_{j,t} \tag{4}$$

$$EoP\ net\ trades_{j,t} = EoP\ stock\ buys_{j,t} - EoP\ stock\ sales_{j,t} \tag{5}$$

We expect EoP total trades to be closely related to stock turnover. EoP net trades, on the other hand, are computed to examine whether stocks receive relatively more buy than sell trades. Such trade imbalances have been associated with stock price movements.

For ease of exposition, we decompose EoP net trades into two variables. The variable EoP net trades^{+} captures positive net trades, while EoP net trade^{-} measures the absolute value of negative net trades.

[17] Note that our sale measure might be less accurate than our buy measure since we are unable to capture sales of stocks that are neither disclosed on the portfolio of the previous nor of the current month.

3.3 Summary statistics

Table 1 shows summary statistics for common fund and stock variables. All variables are winsorized at the 1% levels and defined in Appendix A.I. The reported stock variables are computed by first taking the value-weighted mean of all stocks in each fund's portfolio and then by averaging across funds.

*** Insert Table 1 about here ***

Our sample is consistent with the literature: Funds are large, with a mean of $1,083 million of assets under management. The average fund is relatively old (12 years) and is part of a fund family (75%). Given a mean turnover ratio of 90%, almost the entire portfolio, on average, is turned over once a year. Fund buys and fund sales in the last three days of a reporting period average at about 1% of TNA. However, the relatively high standard deviation implies that some funds trade a substantially higher fraction of their TNA at the end of the period. The majority of funds in our sample are capital-appreciation funds (50%), followed by growth funds (38%). Smaller proportions of funds follow an income (6%) or total-return investment strategy (6%).

Consistent with Wermers (1999), funds are on average invested in large-cap stocks with a market capitalization of about $36 billion. The average investment targets relatively liquid stocks with an average relative bid–ask spread of 0.146%, an Amihud illiquidity measure of 0.012 and a 3-day trading volume of $500 million. The mean stock in a fund's portfolio has a market beta close to one, implying that funds hold on average the market portfolio. The average stock performance over the past three months is 5% if measured by raw returns or 2.7% if measured by 4-factor alphas. The median stock experiences EoP stock buys and sales of about 0.01% in terms of the stock's market capitalization. Consistent with a growing mutual fund industry, net trades are on average slightly positive at 0.004%. The relative small magnitude of these net trades, however, suggests that the majority of fund buys and sales net out within the fund industry.

3.4 Validation of the stock trade measures

Since the end-of-period trading measures on the stock level are imputed proxies that rely on quarterly holding changes, it is critical to validate these measures before turning to our empirical analysis. For that purpose, we relate the total EoP trades to the stock's actual trading volume. Given that mutual funds own on average 30% of the U.S. equity market, we expect this relation to be sizeable (ICI Investment Company Factbook, 2012).

*** Insert Table 2 about here ***

As shown in columns (1) to (4) of Table 2, our proxy for EoP trades is a statistically significant predictor of (adjusted) stock turnover during the last three days of the reporting period. This relationship even holds after including several control variables that have been used in the turnover literature. The adjusted turnover is the stock's market trading volume over the last three days of the reporting period less the average trading volume of the stock over the 20-day period around the reporting date. We make this adjustment to account for recent turnover fluctuations unrelated to EoP trading.[18] While columns (1) and (2) are based on all observations, we exclude all December observations in columns (3) and (4) as several studies show that the turnover at the end of the calendar year is abnormally low. The relationship between our measure and turnover is also sizeable. Stocks whose total trades are in the top quintile experience a 0.03% to 0.05% increase in turnover. If we assume that mutual funds account for 30% of total turnover, this represents 6% to 10% of the average trading volume effected by mutual funds.

[18] Our results are robust if we do not make this adjustment.

Figure 4 illustrates the relationship between the EoP total trade measure and turnover graphically. For that purpose, we sort stocks into deciles according to how much a stock was traded at the end of a month. Stock observations with the highest EoP trades are assigned to the top and those with the lowest trading volume to the bottom decile. While we observe almost no relationship between turnover and trades in the the lower five quintiles, we observe a strong increase in turnover as we move along the higher deciles. Our measure performs poorly for the lower deciles because those stocks exhibit minimal, if any, differences in EoP trades (see the grey bars in the graph). Across the higher deciles, the difference in the trade measure is stronger, and a clear positive relation between our measure and end-of-period turnover is observable.

*** Insert Figure 4 about here ***

In order to address the concern that the documented link between our measure and turnover is spurious, we report results of a placebo test in columns (5) to (8). In this placebo test we relate the EoP total trade measure to the adjusted stock turnover *one year later.* Supporting the validity our measure, the regression coefficients of our measure are insignificant in all specifications.

4 Empirical results

Our empirical analysis is structured into three parts. First, we explore the extent of end-of-period (EoP) trading by comparing the magnitude of these trades with the average trading volume over the whole reporting period. Second, we analyze potential motives for EoP trades by studying fund and stock characteristics. Finally, we examine whether EoP trading is associated with stock price reactions.

4.1 The extent of end-of-period trading

4.1.1 Distribution of fund observations and non-traders

To compute end-of-period (EoP) trades at the fund level, we rely on balance-sheet data obtained from NSAR forms, which are available twice a year. However, funds report to their shareholders in different months. Hence, fund reporting-ends are distributed over the whole calendar year. Panel A of Figure 1 shows the fraction of funds that report in each month of the year. Most funds report in December and June (about 30% of all observations), followed by roughly 25% of all observations reporting in April and October. 18% of our balance sheet data is observed in June and September, while 6% to 8% of the funds report in each of the other months of the year. Although the reporting periods are somewhat clustered, the number of funds reporting in each month is high given that our data set consists of more than 2,500 funds.

*** Insert Figure 1 about here ***

Panel B shows that in each month a significant number of funds do not trade at their period-ends, ranging from 12% in January and July to 27% in December. While the higher percentage of funds without any EoP trades in December might be due to the clustering of holiday days at the end of the year, it is striking that the low EoP engagement is also found at the other calendar months.

*** Insert Figure 2 about here ***

We examine this further by analyzing whether a fund's avoidance of EoP trades is persistent over time. For that purpose, we select all non-traders at a random time point and follow them through the entire sample period. We then examine how many of these funds continue to avoid trading in other time periods. Figure 2 is based on all funds that have executed zero EoP buys (solid) or EoP sales (dashed line) in the first half of 2004.[19] On average about 50% of these funds also conduct no end-of-period trades in the other periods of the time-series. This pattern is observable for EoP buys and EoP sales to the same extent. It appears that some funds persistently avoid trading at the end of their reporting period.

4.1.2 Realized and expected end-of-period trading

To quantify the extent of EoP trading, we compare EoP buys and sales with an estimated expected value for these volumes. These estimates are obtained by dividing a fund's total six-month purchase or sale volume, which was realized over the previous reporting period, by the number of trading days in the period. We then multiply this number by three to get an estimate over a three day window. As illustrated in Figure 3, the realized EoP trades are in some months above and in other months below the expected trading volume, but the two measures are in general closely related. The realized trades in December are significantly below expectations, indicating that fund managers trade less between Christmas and New Year. Some of the lack of trading in December appears to be shifted to January, when realized EoP trades exceed expected EoP trades strongly. The average trade size in the last three days of a reporting period is sizeable and varies from $5 million in December to almost $20 million in January. Hence, reporting-ends are active trading periods. Finally, we observe that EoP purchases and sales in each month are similar in magnitude. This indicates that most trades can be settled within the mutual fund sector.

*** Insert Figure 3 about here ***

[19] Results are very similar if we consider a different time period to identify non-traders.

4.2 Motives for end-of-period trading

In this section we analyze the motives for end-of-period (EoP) trading. We start by an examination of general characteristics of heavy EoP traders on the fund level. We then inquire into the relationship between fund performance and EoP trading. Finally, we study which stocks are subject to particularly high demand or supply at the end of a period.

4.2.1 End-of-period trading and fund characteristics

Table 3 shows fund characteristics for different levels of end-of-period (EoP) trading. We scale our EoP trade measures in two ways. For the first scaling we use a fund's TNA. Scaling by TNA is useful to identify funds that have a high EoP trading volume in comparison to their portfolio size. For the second scaling, we divide the EoP buys (sales) by the expected 3-day purchase (sale) volume of the fund. The expected values are obtained by taking the average of each fund's total buys (sales) over the last six months. Scaling this way relates the EoP trading volume to the 'usual' trading volume of the fund at other trading days in the period.

In each month, we sort all funds into quintiles according to both measures. Funds with exactly zero EoP fund buys or sales are reported separately, as a sixth group for each measure. This way, low-quintile values are not contaminated by the bulk of non-traders. EoP fund buys are reported on the left half, while EoP fund sales are shown on the right half of the table.

*** Insert Table 3 about here ***

Panel A reports average fund characteristics for quintiles sorted by our EoP trade measures scaled by TNA. The first column of both table halves depicts the average characteristics of all funds with no EoP buys or sales in a given period. While these funds have zero EoP trades by definition, funds in the other quintiles exhibit significant EoP trading. Funds in the highest buy quintile accumulate an average EoP purchase volume of 4.9% of their TNA. Similarly, funds in the highest EoP sale quintile sell on average 4.2% of their portfolio at the end of their reporting period.

Funds that show either no or very large EoP trades manage portfolios that are on average about 50% smaller compared to other funds in the sample. Hence, small funds appear to be more extreme in their EoP trading behavior. Heavy EoP traders display higher turnover ratios throughout the year, suggesting that some EoP activity is simply driven by their higher trading intensity. Interestingly, the average turnover ratio of funds with zero EoP buys and sales is relatively high on the buy and about average on the sell side. Hence, the non-trading activity of some funds at period-ends is unlikely a result from low-turnover strategies.

EoP buys correlate with netflows. While funds with zero EoP buys have negative netflows (i.e. outflows), assets under management grow by about 1.4% for funds with EoP buys in the top quintile. This suggests that some purchases at period-ends result from the investment of fresh capital. On the sell side, there is a similar, but negative relationship between EoP trades and flows. High flows observed in the bottom sale quintile might have helped to avoid some asset sales.

We also find evidence consistent with the hypothesis that EoP trading is related to window dressing.[20] While there is little variation in the disclosed proportion of loser stocks across the different quintiles, the proportion of winner stocks is significantly increasing with the amount of EoP trades.[21] Moreover,

[20] Window dressing refers to the the practice of disclosing more winner and fewer loser stocks in the disclosed portfolio holdings in an attempt to mislead investors. See Section 2 for a more detailed explanation.

[21] Winner stocks are defined as the stocks whose performance over the last quarter ranked in the highest quintile of all sample stocks; loser stocks rank in the lowest.

funds with high EoP trades display higher backward holding return (BHRG) and rank gaps, which are the two standard measures of window dressing in the literature. In contrast, the window-dressing variables stay low for funds that avoid EoP trading.

Finally, we see no evidence that the last-day return of a fund's reporting period is linked to EoP trading. This suggests that EoP trades are largely unrelated to portfolio pumping, which aims at inflating fund returns shortly before disclosure.

In Panel B, we report the same statistics, but quintiles are constructed by scaling the EoP trade measures by the expected amount of EoP buys or sales. By adjusting for the funds' general turnover, we can identify funds executing EoP trades in excess of their usual trading volume. Funds in the first three quintiles have an adjusted EoP trading volume of less than 1, which indicates that their EoP trading is lower than on other days of the period. In contrast, funds in the highest EoP buy or sale quintile show a trading volume that is four times higher than on an average 3-day trading window. These large deviations from expectations are predominantly found among funds with low turnover ratios.

When compared to Panel A, we find a similar relationship between EoP trades and netflows as well as EoP trades and fund size. In line with the findings of Panel A, the last-day fund return remains unrelated to a fund's EoP trading activity. Interestingly, however, the relationship between EoP trading (scaled by expected EoP trades) and our window-dressing indicators is less pronounced. While most window-dressing indicators tend to increase first, they drop significantly for the highest EoP trade quintile. Hence, window dressing does not seem to occur when EoP trades deviate strongly from the typical trading volume. From a window dresser's perspective, the avoidance of these extreme trades makes sense to not raise unnecessary attention by regulators or investors.

In summary, our evidence suggests that EoP trading is related to several motives. While some trades seem to be a byproduct of usual trading or driven by fund flows, others seem to be related to window dressing.

4.2.2 End-of-period trading and fund performance

In this section, we want to examine whether large EoP trades are motivated by information. If this is the case, funds with large EoP trades should achieve positive abnormal returns subsequent to their trades. To test this hypothesis, we construct value-weighted portfolios that are rebalanced each month by selecting all funds whose EoP buys or sales (scaled by TNA or expected EoP buys or sales) were in the top quintile at their latest reporting period.[22] We regress the returns of these portfolios on the (i) market, (ii) size, (iii) value-to-book, and (iv) the momentum factor to asses whether funds with large EoP trades show abnormal performance. The regression results are reported in Table 4.

*** Insert Table 4 about here ***

Columns (1) and (2) of Panel A show an insignificant alpha coefficient (intercept) for both portfolios based on funds with large EoP buys. Hence, heavy EoP buyers do not outperform the market on average. On the sell side, we find that the intercept is negative and statistically significant in column (3), but insignificant in column (4). The portfolios of both regressions are based on all funds with large EoP sales, but sales are scaled by TNA in column (3) and by expected EoP sales in column (4). Hence, underperformance is evident when EoP sales are large in comparison to the size of the portfolios, but not when EoP sales are large in comparison to turnover.

[22] Our results are similar if we construct equally weighted portfolios.

In Panel B, we compare the performance of funds with large EoP trades with the performance of funds with low trading. To that end, we construct portfolios that are long on all EoP buyers or sellers in the top quintile (see Panel A), and short in a portfolio consisting of all EoP buyers or sellers in the bottom quintile. Using these portfolios, we find insignificant alphas when EoP trades are scaled by expected trades, and negative alphas when EoP trades are scaled by TNA. Hence, EoP trades do not improve fund performance, but are, if anything, detrimental. This implies that large EoP trades are on average not driven by the possession of superior information.

4.2.3 End-of-period trading and stock characteristics

Finally, we inquire into the motives for EoP trading by examining the characteristics of stocks that receive large EoP buy and sell orders.

*** Insert Table 5 about here ***

Table 5 relates our end-of-period (EoP) net trade measures to stock characteristics. Recall that positive (negative) EoP net trades obtain when EoP stock buys exceed (fall short of) EoP stock sales. Similar to the analysis on the fund level, we sort stocks into quintiles based on their EoP net trade imbalance. We report stocks with a large demand (positive trade imbalance) and supply overhang (negatve trade imbalance) separately. We find stocks subject to strong EoP activity to be smaller and to have lower trading volumes than stocks with median net trade imbalances. Despite of having smaller market caps and trading volumes, there is no identifiable relationship between the EoP net trade imbalance and the relative bid–ask spread or the Amnihud illiquidity measure. Hence, there is no clear evidence that low liquidity stocks receive heightened demand at the end of a period, which would be expected if funds engage in portfolio pumping.

In line with the previous result that EoP buyers hold a larger proportion of winner stocks in their portfolios, stocks that are heavily bought during the last days of the period tend to have higher past 3-months returns and alphas. In contrast, stocks with large negative trade imbalances tend to have lower past performance. Both the tendency to buy winner and sell loser stocks are consistent with the motive of window dressing.

4.3 The economic impact of end-of-period trading

Previous research suggest that trades by mutual funds can result in stock price movements (see Section 2 for a review of the literature). Therefore, we examine whether stocks that experience large trade imbalances at the period-end experience abnormal price changes.

4.3.1 End-of-period trading and stock prices

We start by regressing each stock's EoP net trade imbalance (EoP buys less EoP sales) on its 4-factor alphas around the end of a reporting period. We use 4-factor alphas to adjust for potential price changes not related to EoP trading. We also account for potential heterogeneity between stocks by including stock fixed effects. To control for time trends or month-specific price changes we include monthly time fixed effects.

*** Insert Table 6 about here ***

As shown in column (1) of Table 6, we find a strong relationship between the EoP net trade imbalance and stock prices. Large net trade imbalances are associated with positive and significant alphas over the last three days of a reporting period. In column (2), we differentiate between positive and negative trade imbalances to identify potential asymmetries on the buy and sell side. Surprisingly, the relationship documented in column (1) is entirely driven by excess trades on the buy side and is not evident among stocks with large negative trade imbalances. This suggests that sufficient outside liquidity accommodates the sell orders.[23]

The correlation between alphas and the positive net trade imbalance is economically sizeable. As documented in columns (3) and (4), stocks whose net trade imbalance is in the top decile or whose positive net trade imbalance is in the top tercile experience on average alphas that are 21 and 14 bps higher compared to the remaining stocks in the sample.

*** Insert Figure 5 about here ***

Columns (6) to (8) as well as Figure 5 show that the observed price increase on the buy side is followed by significant reversals. For example, alphas revert by about 12 bps for stocks with the highest net trade imbalance (top decile) over the following three days. That stock prices are only temporary inflated is consistent with stock price movements arising due to price pressure. It is inconsistent with a reverse causality explanation, according to which mutual funds buy stocks only after the price inflation took place. It also supports our previous findings that EoP trades are not motivated by fund managers' ability to access new information faster than the market.

Next, we study whether the price effect is observable throughout the calendar year and whether the reversal effect persists over a longer time period. In Panel A of Table 7, we again report regressions results based on all observations, but measure the stock price reaction over up to 30 days. We then split our data into sub-samples. Panel B reports results based on December observations only, while we use a sub-sample of June observations in Panel C. Regressions using only the other months of the calendar year result in coefficients that are very similar to Panel D. Therefore, we do not report these regressions separately. Finally, in Panel E all observations are included,

[23] The theoretical literature does not offer a clear explanation for this asymmetry.

and interaction dummies capture the difference of the stock-price sensitivity to EoP trades in June or December.

*** Insert Table 7 about here ***

Column (1) of Table 7 shows that the net trade imbalance is positively correlated with stock returns over the last three days of a period in all specifications. Moreover, as evident in Panel E, the December and June interaction terms are insignificant, suggesting that the price increase of stocks with high net trade imbalances prior to the reporting date is of similar magnitude in all months of the year. However, a significant long-term price reversal arises only for trades initiated in December and June. This is noteworthy as it suggest that the economic impact of EoP trading differs across the year. Appendix A.II shows that this difference is unlikely driven by different sample compositions across the calendar months as fund characteristics between funds that report in December and June are very similar to those that report in the other months of the year. Finally, we observe that the reversal effect in December and June is persistent. Even 30 days after the reporting date stock prices are negatively correlated with a stock's net trade imbalance.

4.3.2 End-of-period trading, stock prices and liquidity

To further investigate the hypothesis that the temporary price impact observed in June and December is driven by price pressure rather than by fundamental information, we analyze the price impact and reversal among stocks with different liquidity. Our hypothesis implies that more liquid stocks will suffer less price impact, and recover faster from any price increase. We employ five liquidity proxies: market cap, stock turnover, Amihud's illiquidity measure, the relative bid–ask spread, and a bid–ask proxy suggested by Corwin and Schultz

(2012).[24] For each of these measures we split the sample at the median and report the regression coefficients around period-ends for the two sub-samples separately. Panel A reports the regression results using all observations, while the regressions in Panel B are based on December and June observations alone.

*** Insert Table 8 about here ***

In both Panels we observe a stronger relation between the positive net trade imbalance and 3-day alphas in the last three days of a period for stocks with lower market caps, lower trading volumes, a higher Amihud illiquidity measure, and higher bid-ask spreads. Hence, across all liquidity measures more liquid stocks with high net trade imbalances experience a lower price impact, when compared to less liquid stocks. Panel B shows that liquidity is also related to the speed of the price reversal. While the reversal effect of less liquid stocks becomes significant only after 30-days, more liquid stocks already exhibit statistically significant price reversals one day after the reporting-end. This evidence strongly supports the notion that prices are inflated due to temporary price pressure.

4.3.3 End-of-period trading, stock prices and fund characteristics

Finally, we examine whether the observed temporary price effects in December and June can be linked to certain fund characteristics. For that purpose, we split our sample funds into above and below-median sub-samples for five fund variables. For each fund variable, we construct two trade imbalance measures: One that captures all trades by above-median funds and one that is based on all trades by funds for which the fund variable in interest is below the median. We label the net trade imbalance that arises from trades by above-median funds with the subscript *high* and the net trade imbalance caused by below-

[24] The bid–ask estimator uses the high and low stock price during a trading day and is supposed to be a better estimate than bid–ask spreads observed at the end of a trading day.

median funds with the subscript *low*. We regress each stock's 4-factor alpha on both measures and test for statistical significance between the two regression coefficients.

*** Insert Table 9 about here ***

In Panel A and B, we examine whether the sensitivity between net trades and stock alphas differs across trades that originate from funds with high and low backward holding return (BHRG) and rank gaps. If window dressing is related to the EoP price effect,the effect of net trade imbalance on stock prices should be stronger for trades from funds whose rank and return gap lies above the median. However, the coefficients of both net trade measures are very similar. Neither the initial price increase, nor the long-term reversal effect seems to be related to having high or low window-dressing indicators. The only observable difference is that trades by funds with high rank gaps seem to be related to a quicker price reversal. This effect, however, is not observable when window dressing is measured by backward holding return gaps.

In Panel C, we report similar regression estimates, but split funds according to last-day fund returns. If the price inflation is driven by portfolio pumping, funds with high last-day returns should be the predominant source of price pressure. While the regression coefficient that measures the price *increase* is larger for trades by funds with high last-day returns, there is no difference among the regression coefficients that measure the reversal. Moreover, the relation between 3-days alphas prior to disclosure and the net trade imbalance measure remains statistically significant even if the net trade imbalance is computed by using trades by low-return funds. Hence, while we cannot exclude that some of the price effect is related to portfolio-pumping, portfolio-pumping does not appear to be exclusively responsible for the price appreciations.

Since funds flows have been associated with price pressure (e.g. Coval and Stafford 2007), we follow the same methodology as before to differentiate between trades by funds that receive netflows above and below the median. In all regressions the regression coefficients for $EoP\ net\ trades^{+}_{high}$ and $EoP\ net\ trades^{+}_{low}$ are not statistically different from each other. Hence, the increase and reversal of stock prices is unlikely driven by flow-induced trading.

5 Robustness

Our results on the stock level are robust to the following three alternative specifications.[25] First, we obtain similar results if our stock level measures are scaled by a stock's average turnover over the past year, instead of dividing by the stock's market capitalization. Second, our findings are comparable if we relate stock returns to EoP stock buys instead of using a net trade balance (buys less sales). Finally, the relationship between our trade measures and stock prices is similar when we adjust the stock returns only by a one or three factor model.

6 Conclusion

We show a novel way to measure the trading activity of mutual funds at the end of their reporting periods. Using this measure, we find substantial cross-sectional variation in the end-of-period (EoP) trading activity across funds. While some funds persistently avoid any trading before their disclosure date, the trading volume at period-ends is more than four times higher than on an average trading day for about 20% of the reports.

These large end-of-period trades do not seem to be driven by possessing proprietary information about the stocks' fundamentals as the subsequent

[25] All results are available upon request.

performance of heavy end-of-period traders tends to be worse than the performance of funds with a low trading activity.

Inquiring further into the motives for EoP trading, we find that large purchase or sell orders at period-ends are positively correlated with a fund's backward holding return and rank gap, as well as with the proportion of disclosed winner stocks in the fund's portfolio. All of these measures have been used in the literature to identify window dressing.

We also find evidence for flow-induced trading immediately before disclosure. Funds with large EoP buys receive disproportionally larger inflows, while funds with large EoP sales exhibit lower net flows. This suggest that some end-of-period trades are initiated in order to manage liquidity.

While our findings suggest that EoP trading activity by funds is related to their flows and to window dressing, we do not find evidence that large EoP buys are associated with portfolio pumping, the attempt to inflate fund returns shortly before disclosure. EoP purchases are neither associated with larger funds returns at the last day prior to reporting, nor are they targeted towards particularly illiquid stocks as portfolio pumping would predict.

We also asses whether aggregate EoP trades are linked to stock price reactions. Based on a 4-factor return model, we find stocks that experience a large demand overhang to appreciate in price by about 20 bps over the last three days of the reporting period. This price increase reverts over the following month for December and June reports. Less liquid stocks show stronger price appreciations and slower reversals. These findings are consistent with stock price movements being caused by price pressure.

Finally, we investigate whether the relationship between end-of-period trades and stock prices can be linked to window dressing, flows, or portfolio pumping. Price reactions remain similar even if we focus on the trades of funds that experience large fund netflows, that have low window-dressing indicators, and that are least likely to be engaged in portfolio pumping. Hence, the documented price effect goes above and beyond the effect of familiar stories. We leave the further exploration of the stock price reaction to future research.

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Appendix

A.1 Figures

Figure 1: Funds reporting end-of-period fund buys and sales by months

Panel A shows the number of end-of-period (EoP) observations of our sample funds by calendar month as a fraction of the total number of sample observations. Panel B shows which fraction of those funds report exactly zero trades during the last three days of a reporting period, again broken down by calendar month. Both panels are based on 34,734 observations by 2,966 distinct funds.

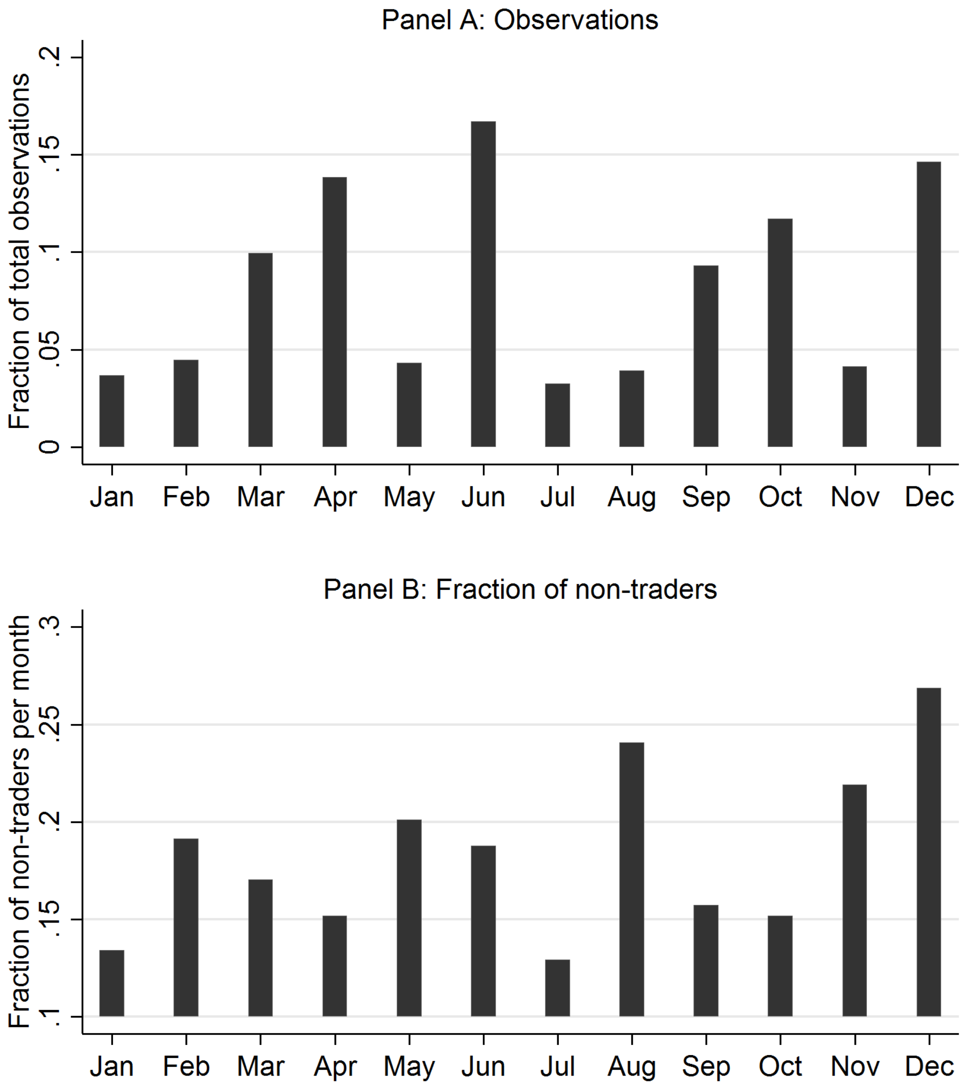


Figure 2: Funds with no end-of-period buys and sales

This figure contains only funds that report zero end-of-period (EoP) fund buys (solid line) or sales (dashed line) in the first half of 2004. The solid (dashed) line shows which fraction of these funds do not show EoP buys (sales) during other time periods. The EoP fund buy (sale) measure is defined in Section 3.2.1 and captures the total purchase (sale) volume for a given fund during the last three days of the fund's reporting period as a percentage of total net assets.

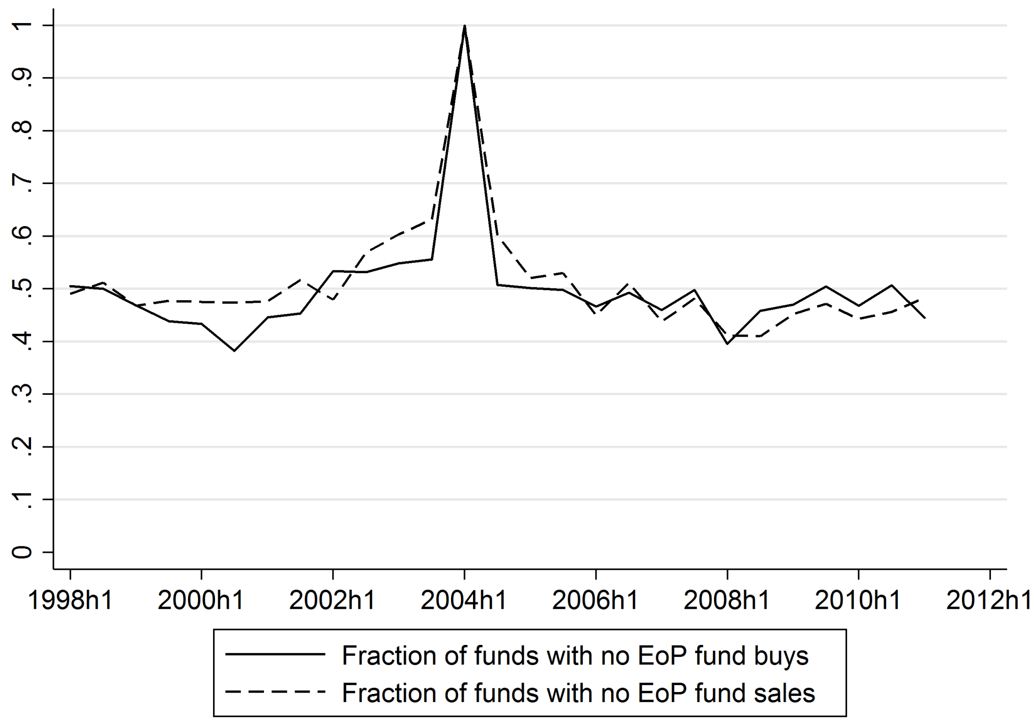


Figure 3: Expected and realized end-of-period fund buys and sales

Panel A (B) reports both expected and realized average volumes of end-of-period fund buys (sales) by calendar month. The EoP fund buy (sale) measure is defined in Section 3.2.1 and captures the total purchase (sale) volume for a given fund during the last three days of the fund's reporting period as a percentage of total net assets. Expected fund buys (sales) are each fund's average 3-day buy (sale) volume over the last six months. Both panels are based on 34,734 observations by 2,966 distinct funds.

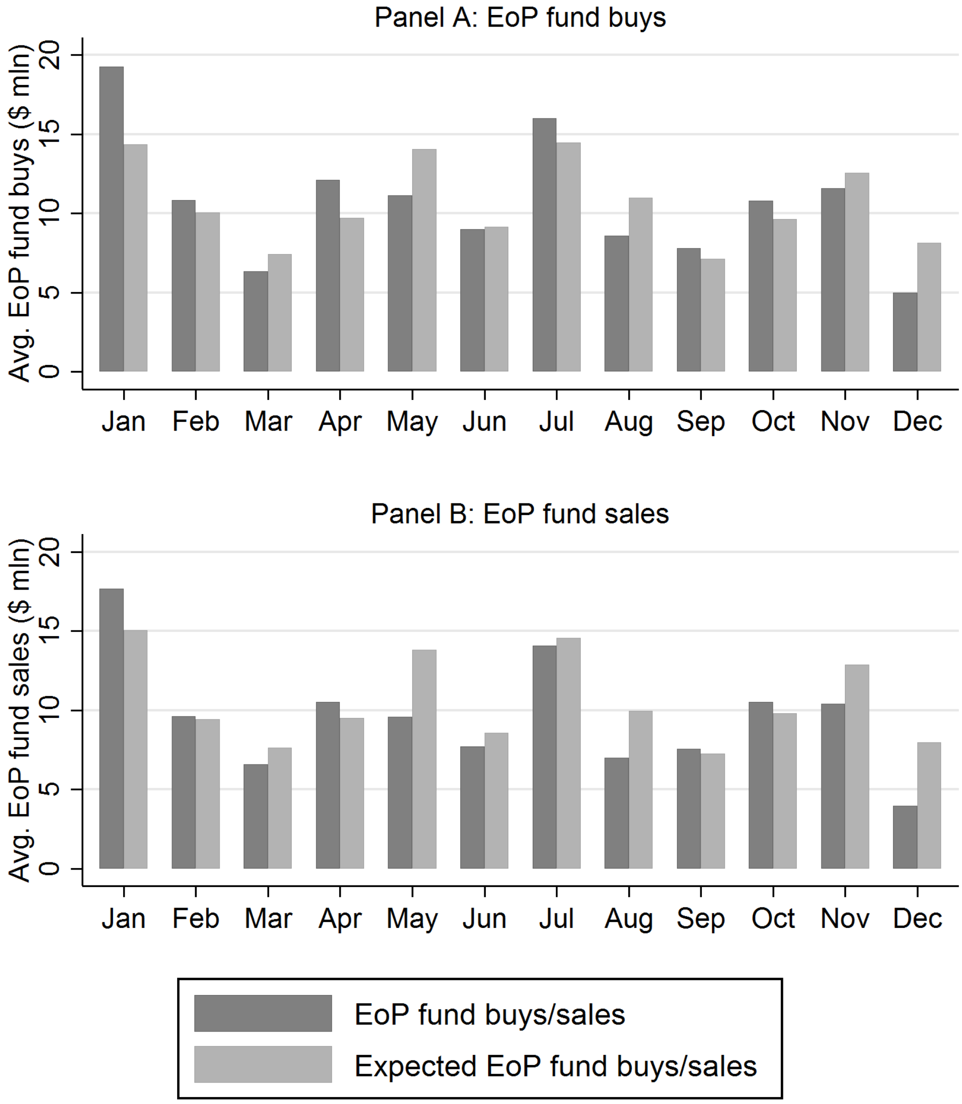


Figure 4: End-of-period trades and the trading volume of stocks

This figure shows the average adjusted trading volume for stocks sorted into 10 deciles according to each stock's end-of-period (EoP) total trade measure. The EoP total trade measure is defined in Section 3.2.2 and captures the imputed total trade volume for a given stock by our sample funds in the last three days of their reporting periods. The adjusted EoP stock trading volume is the difference between the volume of shares traded at the last three days of a period and the average three day share volume over the 20 days around the period-end, scaled by total shares outstanding. All deciles are based on 8,447 distinct stocks and are redefined each month over the sample period from 1998 to 2011. December observations are excluded.

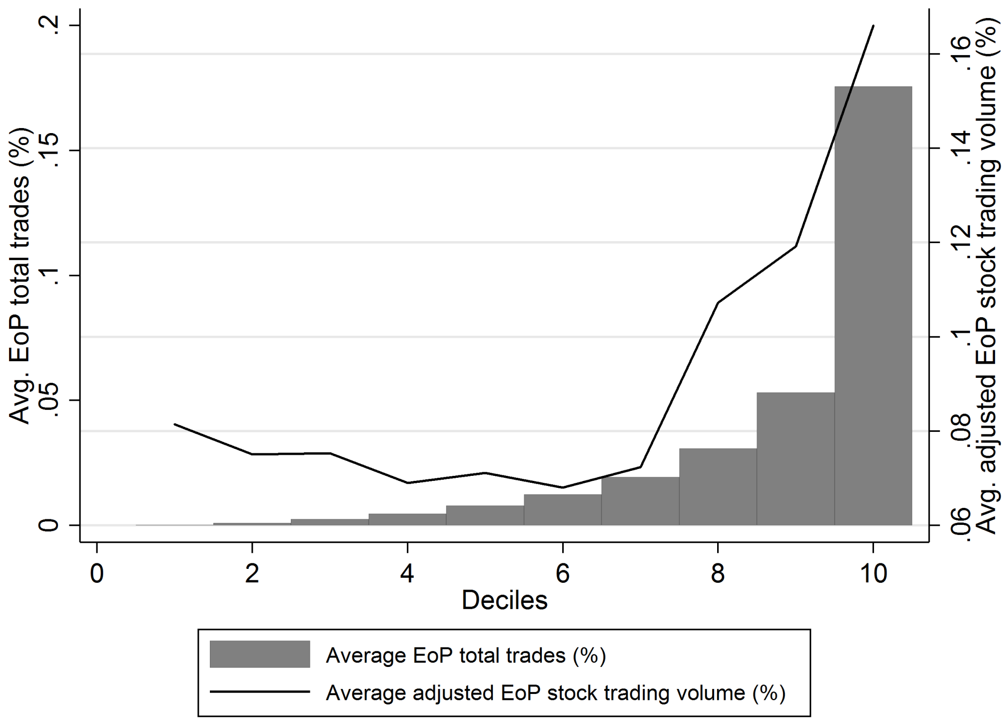
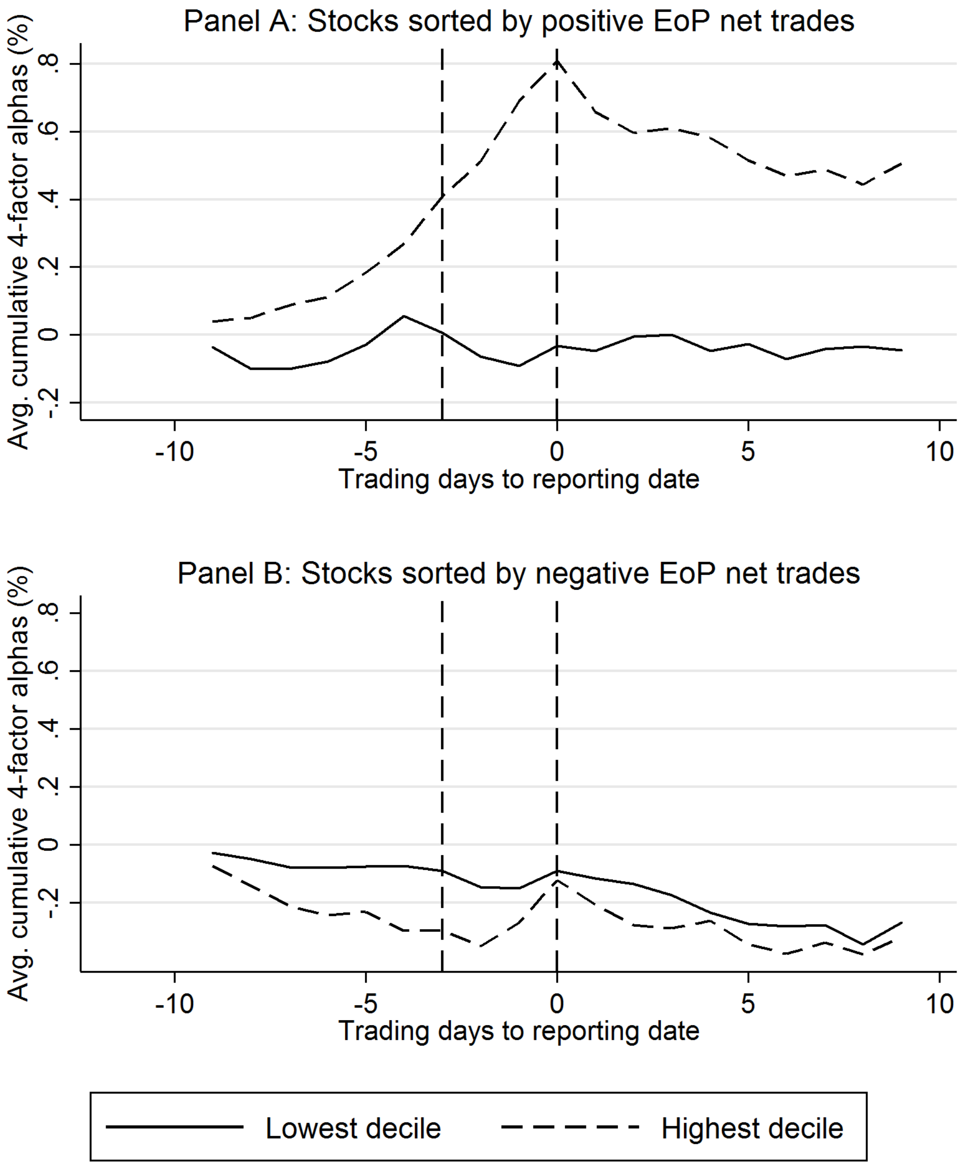


Figure 5: End-of-period net trades and stock returns

These figures show averages of cumulative 4-factor alphas around the end of reporting periods ($t = 0$) for stocks belonging to the first and tenth decile of positive (Panel A) and negative EoP net trades (Panel B). The EoP net trade measure is defined in Section 3.2.2 and captures the imputed volume of total purchases less total sales for a given stock induced by our sample funds in the last three days of their reporting. The betas obtained to calculate 4-factor alphas are estimates from 4-factor regression using daily returns over the last 250 trading days. All deciles are redefined each month over the sample period from 1998 to 2011, covering a total of 8,447 distinct stocks.



A.2 Tables

Table 1: Descriptive Statistics

This table reports descriptive statistics for fund and stock characteristics of 2,508 distinct open-end equity funds from 1998 to 2011. Panel A contains summary statistics on the fund level. Panel B shows stock characteristics of the funds' holdings, which are computed as averages across funds, taking the value weighted average of all stocks in each fund portfolio. All variables are defined in Appendix A.I.

	Open-end fund observations from 1998 to 2011			
	Mean	p50	Sd	#
Panel A: Fund characteristics				
TNA ($ millions)	1,083	186	2,828	21,928
Age (years)	12.061	8.005	13.249	21,928
Fund family (%)	75.583	100.000	42.960	21,387
Turnover ratio (%)	90.401	68.000	80.943	20,095
EoP fund buys (%)	1.181	0.441	1.982	21,842
EoP fund sales (%)	0.998	0.350	1.676	21,831
Capital appreciation (%)	50.275	100.000	50.000	21,301
Growth (%)	37.841	0.000	45.662	21,301
Income (%)	5.866	0.000	16.881	21,301
Total return (%)	6.018	0.000	23.783	21,301
Panel B: Stock characteristics (weighted averages across portfolio holdings)				
Market cap ($ billions)	36.208	31.860	32.107	21,928
3-day turnover ($ millions)	511.766	209.336	609.919	21,928
3-month returns (%)	5.312	5.052	12.472	21,928
3-month 4-factor alphas (%)	2.686	1.729	6.714	21,928
Market beta	1.028	1.022	0.178	21,928
Rel. bid-ask (%)	0.146	0.068	0.263	21,928
Amihud illiquidity	0.012	0.000	0.198	21,928
EoP stock buys (%)	0.017	0.013	0.018	21,928
EoP stock sales (%)	0.013	0.010	0.013	21,928
EoP net trades (%)	0.004	0.002	0.015	21,928
EoP net trades^{+} (%)	0.020	0.015	0.022	21,928
EoP net trades^{-} (%)	-0.016	-0.012	0.017	21,928

Table 2: End-of-period trades and the trading volume of stocks

This table reports OLS regressions relating a stock's imputed end-of-period (EoP) trades to its adjusted trading volume. In columns (1) to (4), the dependent variable is the adjusted 3-day stock turnover at the end of the respective month. The dependent variable in columns (5) to (8) is the adjusted 3-day turnover at the end of the month of the following year. In regressions (3), (4), (7) and (8), December observations are excluded. The EoP total trade measure is defined in Section 3.2.2 and captures the imputed total trade volume for a given stock by our sample funds in the last three days of their reporting periods. $Topquintile(EoP\ total\ trades)$ is a dummy variable that equals one if a stock's EoP trade measure is in the top quintile of the respective month. The adjusted EoP stock trading volume is the difference between the volume of shares traded at the last three days of a period and the average three day share volume over the 20 days around the period-end, scaled by total shares outstanding. All other variables are defined in Table A.I. T-Values are reported in parentheses. Standard errors are heteroskedasticity robust and clustered at the stock level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	3-day adjusted trading volume at EoP				3-day adjusted trading volume at EoP of next year			
	All observations		Excluding December		All observations		Excluding December	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EoP total trades	36.37***		43.40***		5.78		-2.80	
	(2.75)		(3.00)		(0.50)		(-0.22)	
Top quintile(EoP total trades)		0.03*		0.05**		-0.00		-0.02
		(1.90)		(2.33)		(-0.18)		(-0.68)
Alpha	-2.42*	-2.47*	-1.44	-1.50	-1.21	-1.23	-0.99	-1.00
	(-1.81)	(-1.85)	(-0.98)	(-1.01)	(-0.94)	(-0.95)	(-0.70)	(-0.71)
Systematic risk	-2.55***	-2.56***	-1.89***	-1.89***	0.09	0.08	0.64	0.64
	(-6.53)	(-6.54)	(-4.45)	(-4.46)	(0.22)	(0.22)	(1.47)	(1.47)
Idiosyncratic risk	4.67***	4.71***	5.93***	5.97***	-0.38	-0.37	0.01	0.02
	(8.83)	(8.90)	(10.15)	(10.20)	(-0.74)	(-0.71)	(0.02)	(0.03)
Ln(Stock price)	-0.01	-0.01	0.02	0.02	-0.03**	-0.03**	-0.03**	-0.03*
	(-0.84)	(-0.80)	(1.31)	(1.35)	(-2.43)	(-2.35)	(-1.98)	(-1.95)
Ln(Mcap)	0.01	0.01	0.03*	0.03*	0.02	0.02	0.02*	0.02*
	(0.93)	(0.97)	(1.84)	(1.88)	(1.52)	(1.44)	(1.81)	(1.77)
Return autocorrelation	0.11***	0.11***	0.14***	0.14***	-0.00	0.00	-0.01	-0.01
	(4.98)	(5.03)	(5.58)	(5.62)	(-0.01)	(0.00)	(-0.43)	(-0.43)
N	198,117	198,117	172,764	172,764	168,557	168,557	147,371	147,371
Adjusted R^2	0.0789	0.0788	0.0631	0.0630	0.0841	0.0841	0.0719	0.0719
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 3: End-of-period trades and fund characteristics

This table reports mean values of fund characteristics for funds sorted into 5 quintiles according to each funds's measure for end of period (EoP) fund buys (left) and sales (right). The EoP fund buy (sale) measure is defined in Section 3.2.1 and captures the total purchase (sale) volume for a given fund during the last three days of the fund's reporting period as a percentage of total net assets. The adjusted EoP fund buy (sale) is the difference between EoP fund buys (sales) and the average 3-day purchase (sale) volume of the fund over the last six months. Funds with no end-of-period buys or sales are grouped into the 'no buys' or 'no sales' category. All other fund characteristics are defined in Appendix A.I. All quintiles are redefined each month over the sample period from 1998 to 2011 and are based on a total of 2,508 distinct funds.

	Quintiles by EoP fund buys						Quintiles by EoP fund sales					
	None	Q1 (low)	Q2	Q3	Q4	Q5 (high)	None	Q1 (low)	Q2	Q3	Q4	Q5 (high)
Panel A: Quintiles sorted by EoP fund trading scaled by TNA												
EoP fund buys/sales (%)	0.000	0.133	0.467	0.940	1.773	4.867	0.000	0.109	0.407	0.839	1.582	4.247
TNA ($ millions)	451	1,884	1,732	1,165	858	516	482	1,899	1,641	1,196	927	558
Turnover (%)	60.17	27.73	34.08	41.89	53.40	77.99	38.95	65.13	33.64	41.52	54.31	82.22
Netflows (%)	-0.11	0.26	0.51	0.69	1.44	4.18	1.62	1.24	0.79	0.68	0.70	0.24
Winner proportion (%)	16.78	18.37	18.91	20.03	21.23	23.92	17.13	18.48	18.91	20.03	21.26	23.45
Loser proportion (%)	10.09	10.24	10.74	10.59	10.62	9.78	10.06	10.20	10.48	10.51	10.53	10.35
Rankgap (%)	0.509	-0.949	-0.595	0.200	0.975	2.493	-0.230	-0.983	-0.407	0.221	1.344	3.505
BHRG (%)	2.64	2.72	3.04	3.46	4.12	5.08	2.57	2.66	2.94	3.49	4.15	5.33
Last day fund return (%)	0.06	0.14	0.15	0.18	0.19	0.16	0.07	0.11	0.16	0.20	0.19	0.16
Panel B: Quintiles sorted by EoP fund trading scaled by expected EoP trading												
Adj. EoP fund buys/sales (%)	0.000	16.719	51.625	91.477	152.563	391.086	0.000	15.073	48.411	86.545	145.343	387.554
TNA ($ millions)	451	1,229	1,446	1,522	1,329	887	482	1,285	1,508	1,512	1,299	854
Turnover (%)	60.17	51.15	51.14	48.42	47.32	35.77	38.95	87.82	52.19	51.31	48.97	36.26
Netflows (%)	-0.11	0.31	0.41	0.71	1.28	2.65	1.62	-0.01	0.07	0.19	0.59	1.57
Winner proportion (%)	16.78	19.93	20.26	20.34	21.17	19.80	17.13	19.91	20.29	21.07	20.86	19.32
Loser proportion (%)	10.09	10.24	10.63	10.73	10.30	10.07	10.06	10.50	10.12	10.52	10.10	10.78
Rankgap (%)	0.509	0.620	0.873	0.422	0.231	-0.471	-0.230	0.436	1.143	1.484	0.603	-0.417
BHRG (%)	2.64	3.41	3.75	3.67	3.91	3.21	2.57	3.40	3.68	4.02	3.93	3.16
Last day fund return (%)	0.06	0.14	0.15	0.17	0.14	0.13	0.07	0.14	0.11	0.17	0.17	0.16

Table 4: End-of-period trades and fund performance

This table reports OLS regressions relating end-of-period (EoP) trades to fund performance. The EoP fund buy (sale) measure is defined in Section 3.2.1 and captures the total purchase (sale) volume for a given fund during the last three days of the fund's reporting period. The dependent variables are portfolio returns in excess of the risk-free rate. The portfolio return in Panel A is the value-weighted return of all sample funds whose EoP buys (columns 1 and 2) or sales (columns 1 and 3) belong to the highest quintile according to the fund's last reporting date, and is rebalanced each month. The portfolios in Panel B are based on a long position in the top quintile buy portfolio (columns 1 and 2) or sale portfolio (columns 3 and 4) and a short position in the bottom quintile buy or sale portfolio. Returns are measured in a monthly frequency starting and ending always three trading days prior to month-end. Portfolio returns are regressed on the (i) the market, (ii) size, (iii) value-to-book and (iv) momentum factor. T-Values are reported in parentheses. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	Portfolio returns (%)			
	based on EoP buys, scaled by		**based on EoP sales, scaled by**	
	TNA	**E[EoP buys]**	**TNA**	**E[EoP sales]**
	(1)	(2)	(3)	(4)
Panel A: Top EoP buy/sale quintile				
Intercept (%)	-0.03	0.14	-0.27**	0.10
	(-0.23)	(1.38)	(-2.18)	(0.84)
R_m - R_f (%)	1.00***	0.97***	1.01***	0.93***
	(37.73)	(42.92)	(37.79)	(34.98)
SMB (%)	0.20***	0.07**	0.17***	0.19***
	(5.32)	(2.32)	(4.62)	(5.24)
HML (%)	-0.07**	0.05*	-0.09**	0.04
	(-1.99)	(1.66)	(-2.46)	(1.11)
UMD (%)	0.08***	0.04**	0.07***	0.03
	(3.80)	(2.28)	(3.30)	(1.56)
N	153	153	153	153
Adjusted R^2	0.928	0.939	0.928	0.917
Panel B: Long in the top EoP buy/sale quintle, short in the bottom quintile				
Intercept (%)	-0.34**	-0.14	-0.65***	-0.16
	(-2.52)	(-1.03)	(-4.18)	(-1.22)
R_m - R_f (%)	0.08***	0.01	0.08**	-0.03
	(2.84)	(0.36)	(2.35)	(-1.09)
SMB (%)	0.20***	0.08**	0.12**	0.11***
	(4.93)	(2.09)	(2.47)	(2.69)
HML (%)	-0.07*	0.12***	-0.19***	0.01
	(-1.82)	(3.08)	(-4.27)	(0.27)
UMD (%)	0.13***	0.07***	0.10***	0.08***
	(5.52)	(3.06)	(3.58)	(3.19)
N	153	153	153	153
Adjusted R^2	0.384	0.0898	0.308	0.116

Table 5: End-of-period net trades and stock characteristics

This table reports mean values of stock characteristics for stocks sorted into quintiles according to each stock's positive (left) and negative (right) end-of-period (EoP) net trades (left). The EoP net trade measure is defined in Section 3.2.2 and captures the imputed volume of total purchases less total sales for a given stock induced by our sample funds in the last three days of their reporting period. EoP net trades^{+} contain all positive EoP net trades, while EoP net trades^{-} denote all negative EoP net trades. Quintiles are based on 289,718 obersvations of 8,447 distinct stocks and are redefined each month over the sample period from 1998 to 2011. All stock characteristics are defined in Appendix A.I.

	Quintiles sorted by EoP net trades^{+}					**Quintiles sorted by EoP net trades^{-}**				
	Q1 (low)	Q2	Q3	Q4	Q5 (high)	Q1 (low)	Q2	Q3	Q4	Q5 (high)
EoP net trades										
EoP net trades$^{+/-}$	0.000	0.002	0.007	0.018	0.077	0.000	0.002	0.006	0.017	0.078
Size measures										
Market cap ($ billions)	5.23	6.12	5.45	4.14	2.81	5.48	6.35	6.00	4.61	2.77
Avg. 3-day turnover ($ millions)	100.94	130.85	130.21	115.43	94.92	102.82	137.73	145.41	134.34	102.26
Performance measures										
3-month returns (%)	4.067	4.405	4.894	6.013	6.338	0.801	1.282	1.239	0.655	-0.179
3-month alphas (%)	1.035	1.148	1.486	2.556	3.038	-1.496	-1.373	-1.239	-1.893	-2.835
Market beta	0.96	0.97	1.00	1.01	0.99	0.96	0.99	1.00	1.00	0.98
Liquidity measures										
Rel. bid-ask (%)	0.4442	0.3929	0.3509	0.3273	0.3290	0.5240	0.4310	0.3413	0.3280	0.3617
Amihud illiquidity	0.1880	0.1460	0.1177	0.0800	0.1009	0.3898	0.2004	0.1236	0.1100	0.1461

Table 6: End-of-period stock trades and stock prices

This table reports OLS regressions relating each stock's imputed end-of-period (EoP) net trades to 4-factor alphas arround the end of a period. The EoP net trade measure is defined in Section 3.2.2 and captures the imputed volume of total purchases less total sales for a given stock induced by our sample funds in the last three days of their reporting period. EoP net trades$^+$ contain all positive EoP net trades, while EoP net trades$^-$ denote all negative EoP net trades. Tercile (deciles) dummies are used to indicate whether a stock observation belongs to the top, mid or bottom tercile (first or tenth decile) of a given variable in the respective month. 4-factor alphas are computed using each stock's betas to the (i) the market, (ii) size, (iii) value-to-book and (iv) momentum factor which are estimated using the previous 250 trading days. T-Values are reported in parentheses. Standard errors are heteroskedasticity robust and clustered at the stock level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	4-factor alphas (%)							
	between t and $t-3$				between t and $t+3$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EoP net trades(%)	1.33***				-0.36			
	(3.68)				(-0.93)			
EoP net trades$^+$(%)		2.34***				-0.98**		
		(5.71)				(-2.22)		
EoP net trades$^-$(%)		0.70				-0.48		
		(1.52)				(-0.98)		
Highest vol. decile(EoP net trades)			0.21***				-0.12***	
			(5.14)				(-2.97)	
Lowest vol. decile(EoP net trades)			-0.01				-0.05	
			(-0.14)				(-1.19)	
Highest vol. tercile(EoP net trades$^+$)				0.14***				-0.16***
				(4.25)				(-4.50)
Mid vol. tercile(EoP net trades$^+$)				0.06**				-0.08**
				(1.99)				(-2.23)
Mid vol. tercile(EoP net trades$^-$)				-0.10***				-0.11***
				(-2.94)				(-3.08)
Highest vol. tercile(EoP net trades$^-$)				-0.02				-0.11***
				(-0.63)				(-2.85)
N	289,720	289,720	289,720	289,720	289,437	289,437	289,437	289,437
Adjusted R^2	0.0258	0.0258	0.0258	0.0258	0.0235	0.0235	0.0235	0.0235
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: End-of-period stock trades and reversal

This table reports OLS regressions relating each stock's imputed end-of-period (EoP) net trades to 4-factor alphas around the end of funds' reporting periods. The EoP net trade measure is defined in Section 3.2.2 and captures the imputed volume of total purchases less total sales for a given stock induced by our sample funds in the last three days of their reporting period. EoP net trades^{+} contain all positive EoP net trades, while EoP net trades^{-} denote all negative EoP net trades. 4-factor alphas are computed using each stock's betas to the (i) the market, (ii) size, (iii) value-to-book and (iv) momentum factor which are estimated using the previous 250 trading days. Panels A to E show separate regressions based on different sub-samples. T-Values are reported in parentheses. Standard errors are heteroskedasticity robust and clustered at the stock level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	4-factor alphas (%)				
	$[t-3,t]$	$[t,t+1]$	$[t,t+3]$	$[t,t+10]$	$[t,t+30]$
	(1)	(2)	(3)	(4)	(5)
Panel A: All observations (N = 289,720)					
EoP net trades^{+} (%)	2.34***	-0.87***	-0.98**	-1.15	-2.97**
	(5.71)	(-3.52)	(-2.22)	(-1.49)	(-2.19)
EoP net trades^{-} (%)	0.70	-0.13	-0.48	0.34	1.51
	(1.52)	(-0.50)	(-0.98)	(0.38)	(1.04)
Panel B: December observations only (N = 35,360)					
EoP net trades^{+} (%)	3.36***	-0.82	-2.70*	-5.73**	-12.2***
	(2.95)	(-0.97)	(-1.78)	(-2.26)	(-3.13)
EoP net trades^{-} (%)	1.98	-0.27	-2.19	-1.76	-3.77
	(1.20)	(-0.28)	(-1.18)	(-0.62)	(-0.77)
Panel C: June observations only (N = 39,045)					
EoP net trades^{+} (%)	2.13***	-0.16	-1.29	-1.68	-7.14***
	(2.70)	(-0.34)	(-1.50)	(-1.11)	(-2.66)
EoP net trades^{-} (%)	0.80	-0.55	-1.13	0.09	1.67
	(0.78)	(-1.02)	(-1.21)	(0.04)	(0.55)
Panel D: All observations except June and December (N = 211,662)					
EoP net trades^{+} (%)	2.06***	-1.14***	-0.21	0.15	1.83
	(3.79)	(-3.51)	(-0.36)	(0.15)	(1.46)
EoP net trades^{-} (%)	0.53	-0.00	-0.29	-0.29	0.53
	(0.94)	(-0.01)	(-0.47)	(-0.27)	(0.40)
Panel E: All observations (N = 289,720)					
EoP net trades^{+} (%)	2.12***	-0.92***	0.31	0.66	2.28*
	(3.91)	(-2.84)	(0.55)	(0.66)	(1.84)
EoP net trades^{-} (%)	0.46	0.20	0.20	0.03	0.71
	(0.83)	(0.60)	(0.33)	(0.03)	(0.54)
June*EoP net trades^{+} (%)	-0.10	0.87	-2.36**	-2.38	-6.35***
	(-0.11)	(1.60)	(-2.46)	(-1.39)	(-3.06)
June*EoP net trades^{-} (%)	-0.10	-0.91	-1.54	2.00	2.34
	(-0.09)	(-1.51)	(-1.49)	(0.97)	(1.03)
December*EoP net trades^{+} (%)	1.79	-1.39*	-5.07***	-8.87***	-12.4***
	(1.48)	(-1.72)	(-3.45)	(-3.58)	(-4.25)
December*EoP net trades^{-} (%)	2.01	-0.77	-2.23	-1.42	1.29
	(1.27)	(-0.82)	(-1.22)	(-0.50)	(0.37)
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Stock fixed effects	Yes	Yes	Yes	Yes	Yes

Table 8: End-of-period trades, stock returns and liquidity

This table reports OLS regression coefficients relating each stock's positive end-of-period (EoP) net trades to 4-factor alphas around the end of funds' reporting periods. The EoP net trade measure is defined in Section 3.2.2 and captures the imputed volume of total purchases less total sales for a given stock induced by our sample funds in the last three days of their reporting period. EoP net trades$^+$ contain all positive EoP net trades. The regression results reported in Panel A (B) are based on all (only June and December) observations. The respective variable in each row is used to split the sample into two sub-samples containing only observations above (left) and below (right) the median value in a given month. 4-factor alphas are computed using each stock's betas to the (i) the market, (ii) size, (iii) value-to-book and (iv) momentum factor which are estimated using the previous 250 trading days. T-Values are reported in parentheses. Standard errors are heteroskedasticity robust and clustered at the stock level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	4-factor alphas (%)									
	Stock observations above median					Stock observations below median				
	$[t-3,t]$	$[t,t+1]$	$[t,t+3]$	$[t,t+10]$	$[t,t+30]$	$[t-3,t]$	$[t,t+1]$	$[t,t+3]$	$[t,t+10]$	$[t,t+30]$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: EoP net trades$^+$ coefficient based on all months. Stocks are split along the median of the stocks'...										
Market cap	1.3**	-0.9***	-0.2	-1.0	0.1	3.1***	-0.5	-0.7	0.6	-2.9
	(2.55)	(-2.87)	(-0.32)	(-1.07)	(0.07)	(4.70)	(-1.15)	(-1.01)	(0.48)	(-1.32)
Trading volume	2.1***	-1.0***	-0.4	-0.2	-0.2	3.2***	-0.1	-0.2	0.4	-1.7
	(4.28)	(-3.25)	(-0.66)	(-0.22)	(-0.10)	(4.65)	(-0.15)	(-0.20)	(0.34)	(-0.77)
Amihud illiquidity	3.8***	-0.2	-0.3	0.9	-1.9	1.6***	-1.0***	-0.3	-0.7	0.4
	(5.34)	(-0.58)	(-0.44)	(0.68)	(-0.83)	(3.26)	(-3.42)	(-0.56)	(-0.76)	(0.26)
Relative bid-ask	2.7***	-0.3	-0.3	1.3	-3.5	1.1**	-0.6*	-0.8	-2.1**	-3.0*
	(3.66)	(-0.82)	(-0.45)	(0.92)	(-1.44)	(2.38)	(-1.89)	(-1.49)	(-2.32)	(-1.87)
Bid-ask proxy	2.9***	-0.8**	-0.9	-0.3	-2.1	1.5***	-0.8**	-0.9*	-2.2**	-3.6**
	(4.59)	(-2.22)	(-1.32)	(-0.28)	(-0.99)	(3.33)	(-2.54)	(-1.81)	(-2.50)	(-2.36)
Panel B: EoP net trades$^+$ coefficient based on June and December only. Stocks are split along the median of the stocks'...										
Market cap	0.7	-1.4***	-2.6***	-3.9**	-6.2**	5.1***	0.6	0.3	-0.1	-12.3***
	(0.95)	(-3.02)	(-2.93)	(-2.54)	(-2.50)	(4.73)	(0.79)	(0.21)	(-0.06)	(-3.41)
Trading Volume	2.1***	-1.3***	-2.1**	-3.0*	-7.6***	4.5***	0.9	1.0	0.4	-7.4**
	(2.96)	(-2.77)	(-2.32)	(-1.87)	(-2.84)	(4.00)	(1.28)	(0.75)	(0.20)	(-2.06)
Amihud illiquidity	5.2***	0.6	0.1	1.4	-6.8*	1.4**	-1.5***	-1.7**	-3.5**	-8.3***
	(4.41)	(0.83)	(0.08)	(0.62)	(-1.72)	(2.08)	(-3.23)	(-1.97)	(-2.27)	(-3.29)
Relative bid-ask	4.1***	1.3	0.0	-0.1	-12.3***	1.3**	-0.8*	-1.5*	-2.4	-5.8**
	(3.25)	(1.56)	(0.03)	(-0.03)	(-2.80)	(2.02)	(-1.88)	(-1.71)	(-1.58)	(-2.29)
Bid-ask proxy	3.3***	0.8	-0.2	-1.3	-10.4***	2.0***	-0.9**	-2.0**	-2.9**	-5.5**
	(3.09)	(1.20)	(-0.17)	(-0.62)	(-2.83)	(2.98)	(-2.00)	(-2.44)	(-2.07)	(-2.30)
EoP net trades$^-$ included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 9: EoP trades & price reversal across fund characteristics

This table reports OLS regression coefficients relating end-of-period (EoP) net trades to 4-factor alphas around the end of funds' reporting periods. For each variable of Panel A to E, we compute EoP net trades$^{+}{}_{high(low)}$ by aggregating all EoP fund buys net of all EoP fund sales over those funds with the variable above (below) its median value. Thus, we split EoP net trades^{+}into two consistent parts coming from the same number of funds: those that score high vs. low along the five fund characteristics in Panels A to E. The EoP fund buy (sale) measure is defined in Section 3.2.1 and captures the total purchase (sale) volume for a given fund during the last three days of the fund's reporting period. 4-factor alphas are computed using each stock's betas to the (i) the market, (ii) size, (iii) value-to-book and (iv) momentum factor which are estimated using the previous 250 trading days. The regression results reported are based on June and December observations in the sample period 1998-2011. T-Values are reported in parentheses. Standard errors are heteroskedasticity robust and clustered at the stock level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	4-factor alphas (%)					
	$[t-3,t]$	$[t,t+1]$	$[t,t+3]$	$[t,t+10]$	$[t,t+15]$	$[t,t+30]$
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: BHRG						
EoP net trades$^{+}{}_{high}$	3.81***	-0.15	-1.36	-3.04*	-5.23**	-9.80***
	(4.37)	(-0.28)	(-1.33)	(-1.74)	(-2.44)	(-3.17)
EoP net trades$^{+}{}_{low}$	1.81*	-1.31**	-2.38**	-2.34	-5.57**	-9.14***
	(1.84)	(-1.99)	(-1.98)	(-1.11)	(-2.36)	(-2.90)
p-value($high = low$)	0.13	0.18	0.52	0.80	0.92	0.88
Panel B: Rankgap						
EoP net trades$^{+}{}_{high}$	2.20**	-1.75***	-5.08***	-8.16***	-9.90***	-14.2***
	(2.11)	(-2.67)	(-3.93)	(-3.91)	(-3.94)	(-3.75)
EoP net trades$^{+}{}_{low}$	3.43***	0.03	-0.33	-0.71	-3.63*	-8.43***
	(4.20)	(0.06)	(-0.34)	(-0.42)	(-1.84)	(-3.07)
p-value($high = low$)	0.36	0.04	0.00	0.01	0.05	0.22
Panel C: Last day fund return						
EoP net trades$^{+}{}_{high}$	4.22***	-0.70	-2.32**	-2.74	-6.48***	-10.2***
	(4.74)	(-1.18)	(-2.10)	(-1.50)	(-2.93)	(-3.25)
EoP net trades$^{+}{}_{low}$	1.60*	-0.21	-1.36	-2.09	-3.44	-9.24***
	(1.67)	(-0.36)	(-1.27)	(-1.08)	(-1.51)	(-2.88)
p-value($high = low$)	0.05	0.55	0.53	0.81	0.34	0.83
Panel D: 3-month fund flows						
EoP net trades$^{+}{}_{high}$	2.75***	-0.89*	-2.14**	-1.81	-4.85**	-8.76***
	(3.53)	(-1.73)	(-2.22)	(-1.10)	(-2.50)	(-3.13)
EoP net trades$^{+}{}_{low}$	3.26***	0.16	-0.71	-4.67**	-6.34**	-11.9***
	(2.68)	(0.21)	(-0.52)	(-2.00)	(-2.24)	(-3.09)
p-value($high = low$)	0.73	0.27	0.40	0.33	0.67	0.52
EoP net trades^{-}included	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Stock fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

A.3 Variable definitions

Table A.I: Variable Definitions

Variable Name	Definition	Source
End-of-period (EoP) trading measures:		
EoP fund buys$_{\mathrm{it}}$	Payables for instruments purchased of fund i at day t.	NSAR
EoP fund sales$_{\mathrm{it}}$	Receivables from instruments sold of fund i at day t.	NSAR
Shares bought$_{\mathrm{ijt}}$	Quarterly increase in stock j's shares by fund i reported at t.	Thom
Shares sold$_{\mathrm{ijt}}$	Quarterly decrease in stock j's shares by fund i reported at t.	Thom
EoP stock buys$_{\mathrm{jt}}$	Obtained for stock j at day t by the following formula: $\frac{\sum^{i} EoP\ fund\ buys_{i,t}}{\text{Mcap}_{jt}} \cdot \frac{\text{Shares bought}_{ijt} \cdot price_{jt}}{\sum^{k} \text{Shares bought}_{ikt} \cdot price_{kt}}$	NSAR, Thom
EoP stock sales$_{\mathrm{jt}}$	Obtained for stock j at day t by the following formula: $\frac{\sum^{i} EoP\ fund\ sales_{i,t}}{\text{Mcap}_{jt}} \cdot \frac{\text{Shares sold}_{ijt} \cdot price_{jt}}{\sum^{k} \text{Shares sold}_{ikt} \cdot price_{kt}}$	NSAR, Thom
EoP total trades$_{\mathrm{jt}}$	Sum of EoP stock buys and sales of stock j at day t.	NSAR, Thom
EoP net trades$_{\mathrm{jt}}$	Difference between stock j's EoP stock buys and sales at day t.	NSAR, Thom
EoP net trades$^{+}{}_{\mathrm{jt}}$	Maximum of 0 and stock j's EoP net trades at day t.	NSAR, Thom
EoP net trades$^{-}{}_{\mathrm{jt}}$	Minimum of 0 and stock j's EoP net trades at day t, multiplied by -1.	NSAR, Thom
Fund characteristics:		
3-month fund flows$_{\mathrm{it}}$	Sum of monthly netflows over the past three months divided by TNA of the previous quarter, where monthly netflows are computed for fund i at time t by the following formula: $\text{TNA}_{i,t} - \text{TNA}_{i,t-1} \cdot (1 + \text{Fund return}_{i,t})$	CRSP$_{\mathrm{F}}$

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Table A.I: continued from previous page

Variable Name	Definition	Source
Fund 4-factor alpha$_{\text{it}}$	Fund return$_{i,t}$ $-$ $\sum_{k=1}^{4}$ factor return$_{k,t}$ $*$ $\beta_{j,k,t}$, where $\beta_{j,k,t}$ is computed for fund i at time t over the past 250 trading days. The subscript k is used as a label for the following four factors: (i) market, (ii) size, (iii) value-to-book and (iv) momentum factor.	CRSP$_{\text{F}}$, FF
Winner proportion$_{\text{it}}$	Percentage of assets invested by fund i at time t in stocks whose returns over the last quarter were in the top quintile of all sample stocks.	CRSP$_{\text{F,S}}$, Thom
Loser proportion$_{\text{it}}$	Percentage of assets invested by fund i at time t in stocks whose returns over the last quarter were in the bottom quintile of all sample stocks.	CRSP$_{\text{F,S}}$, Thom
Rankgap$_{\text{it}}$	$Return\ rank_{it} - \frac{Winner\ rank_{it} + loser\ rank_{it}}{2}/200$, where winner (loser) rank is computed by assigning a rank to fund i at time t after sorting all sample funds according to each fund's winner (loser) proportion. The rank ranges from 1 to 100 and is highest for funds with the lowest winner (highest loser) proportion. Similarly, the return rank ranges from 1 (highest) to 100 (lowest) and is based on quarterly fund returns.	CRSP$_{\text{F,S}}$, Thom
BHRG$_{\text{it}}$	Quarterly return of a hypothetical portfolio comprising fund i's end-of-quarter holdings at time t less the actual fund return over the quarter.	CRSP$_{\text{F,S}}$, Thom
Stock characteristics:		
Trading volume$_{\text{jt}}$	Average of three day trading volume of stock j over the quarter ending at time t.	CRSP$_{\text{S}}$
Adj. EoP trading vol$_{\text{jt}}$	Difference between the dollar value of shares traded at the last three days of a period and the average three day dollar volume of stock j over 20 days surrounding the reporting date t, scaled by the stock's total shares outstanding.	CRSP$_{\text{S}}$

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Table A.I: continued from previous page

Variable Name	**Definition**	**Source**
Alpha_{jt}	Stock return$_{j,t}$ − factor return$_{k,t} * \beta_{j,k,t}$, where $\beta_{j,k,t}$ is computed for stock j at time t over the past 250 trading days. The subscript k is used as a label for the market factor.	CRSP_{S}, FF
4-factor alpha_{jt}	Stock return$_{j,t}$ − $\sum_{k=1}^{4}$ factor return$_{k,t} * \beta_{j,k,t}$, where $\beta_{j,k,t}$ is computed for stock j at time t over the past 250 trading days. The subscript k is used as a label for the following four factors: (i) market, (ii) size, (iii) value-to-book and (iv) momentum factor.	CRSP_{S}, FF
Systematic risk_{jt}	The coefficient of the market factor of stock j at time t, when regressing the returns of the stock over the past 250 trading days on the market factor.	CRSP_{S}, FF
Idiosyncratic risk_{jt}	The variance of the residuals of stock j at time t, obtained when regressing the returns of the stock over the past 250 trading days on the market factor.	CRSP_{S}, FF
Ret. $\text{autocorrelation}_{\text{jt}}$	The autocorrelation of stock j' returns over the last quarter ending at time t.	CRSP_{S}
Rel. $\text{bid-ask}_{\text{jt}}$	Average of daily relative bid-ask spreads of stock j over the quarter ending at time t, where the daily relative bid-ask spreads are calculated by the following formula: $\frac{Ask-Bid}{(Ask+Bid)/2}$.	CRSP_{S}
Amihud $\text{illiquidity}_{\text{jt}}$	Average of daily illiquidity of stock j over the last quarter ending at time t, where the daily stock illiqudity is calculated by the following formula: $\frac{\lvert Stockreturn \rvert}{(Dollar\ amount\ of\ shares\ trades)/2}$.	CRSP_{S}
Bid-ask proxy_{jt}	Average of daily bid-ask spread proxies of stock j over the quarter ending at time t, where the daily bid-ask spread proxies are calculated by the formula documented in Corwin and Schultz (2012).	CRSP_{S}

A.4 Supplementary results

Table A.II: Descriptive statistics: December and June reporting vs. other reporting months

This table compares the characteristics of funds that report in June and December with funds that report in other calendar months. The descriptive statistics are based on 2,508 distinct open-end equity funds from 1998 to 2011. All variables are defined in Appendix A.I.

	December / June			Other reporting months		
	Mean	p50	#	Mean	p50	#
TNA ($ millions)	1,136.94	210.20	8,114	1,147.58	208.53	12,557
Age (years)	15.51	9.51	8,114	11.30	8.41	12,557
Turnover ratio (%)	83.23	61.00	8,114	95.65	72.80	12,557
Netflows (%)	7.78	-1.66	8,114	7.79	-1.63	12,557
Rankgap	0.00	-0.00	8,114	0.01	0.00	12,557
BHRG (%)	3.73	2.17	8,114	3.20	2.01	12,557
Income (%)	6.85	0.00	8,114	5.36	0.00	12,557
Growth (%)	39.52	0.00	8,114	36.41	0.00	12,557
Capital appreciation (%)	47.23	0.00	8,114	51.64	100.00	12,557
Total return (%)	6.40	0.00	8,114	6.59	0.00	12,557